Indiana University

Interpreting regression models using Stata

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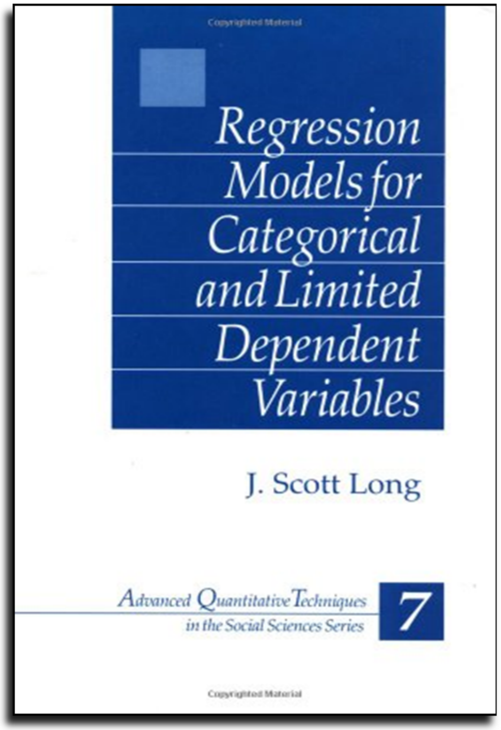
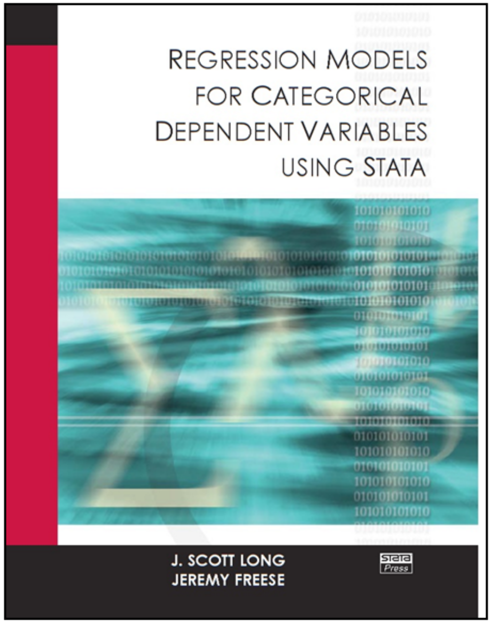
Long-StataCorp-2013-08-11.docx

Interpreting regression models



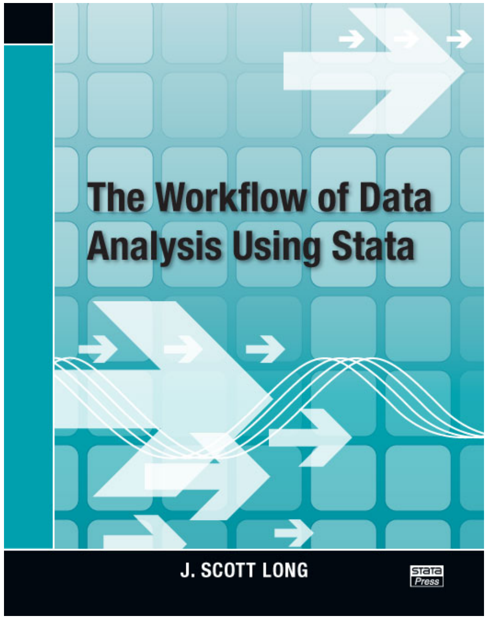
1980s	Interpreting log-linear and multinomial models to support substantive research
1991	*Markov: A Statistical Environment for GAUSS*
1996	change.ado and genpred.ado in Stata 4
1997	*Regression Models for Categorical and Limited Dependent Variables*
1997	*Markov 2.5,* ineffectively supporting the book

Working with StataCorp



1998	Bill Sribney on post-estimation Bill Gould on e(sample)
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*
	Learning how people compute...
2009	Stata 11 with **`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

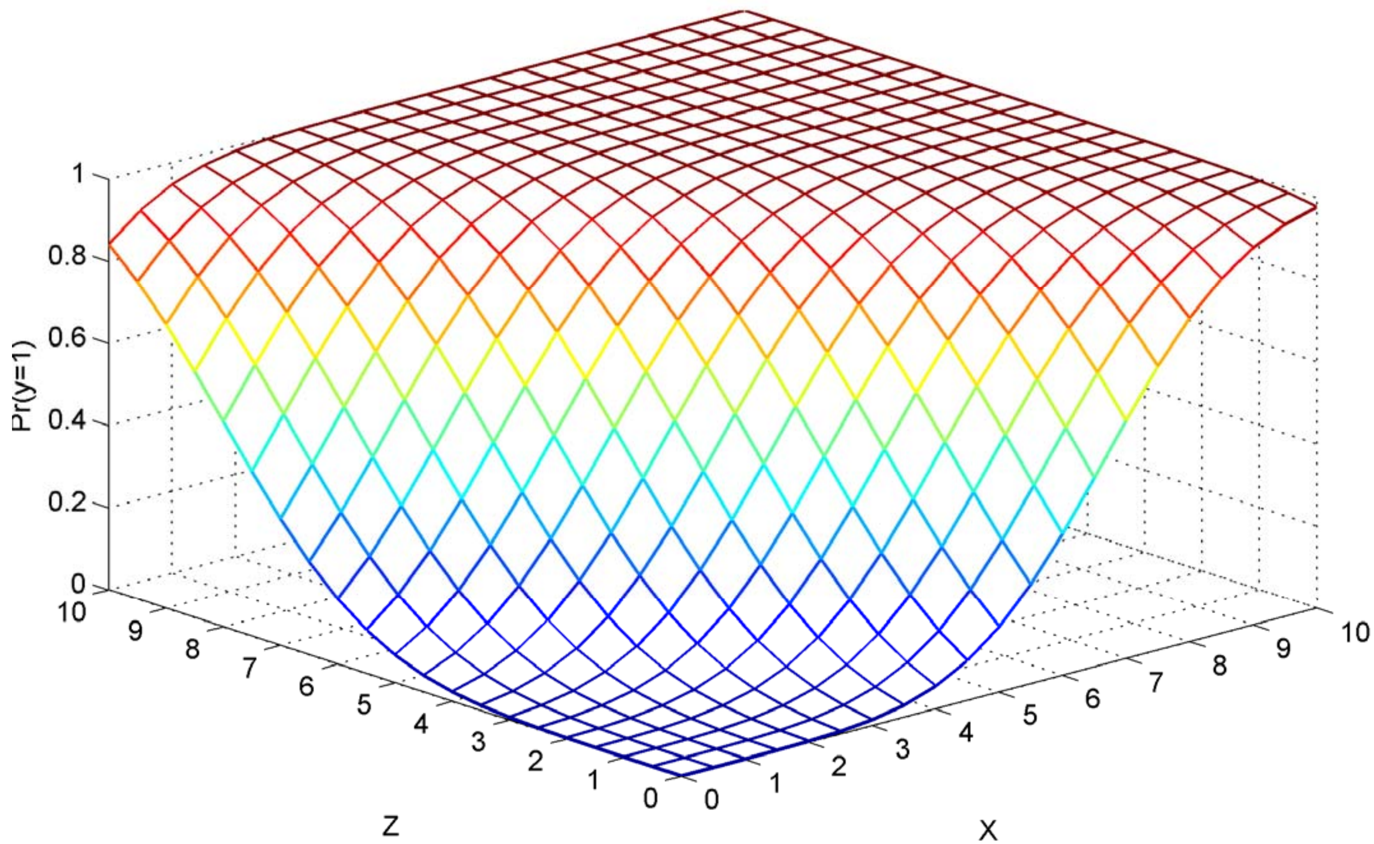
- Did we miss something? Are there better ways to do things?
- Do our new methods of interpretation make sense?
- We want to be "Stata-like"

Other SPost13 commands

- Why we wrote them
- Why we hope they become obsolete.

Things I (we) would 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 for interpretation

Official Stata

`margins`: a remarkable program.

`marginsplot`: making **`margins`** accessible to typical users.

SPost13 wrappers for margins and lincom

`mtable`: tables of predictions.

`mchange`: marginal effects.

`mgen`: predictions to plot.

`mlistat`: compact listing of at() matrix.

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

Why aren't margins and marginsplot and sufficient?

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
                 k5               =           1
                 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)
```

```
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: compact output

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

<= pass through to margins

```
Expression: Pr(lfp)

          |        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
```

Other statistics could be included in the table.

mtable: combined results

```
. 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))

1._at        : yr89            =           0
:::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: combine multiple outcome

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

Expression: Pr(warm)

           |      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
```

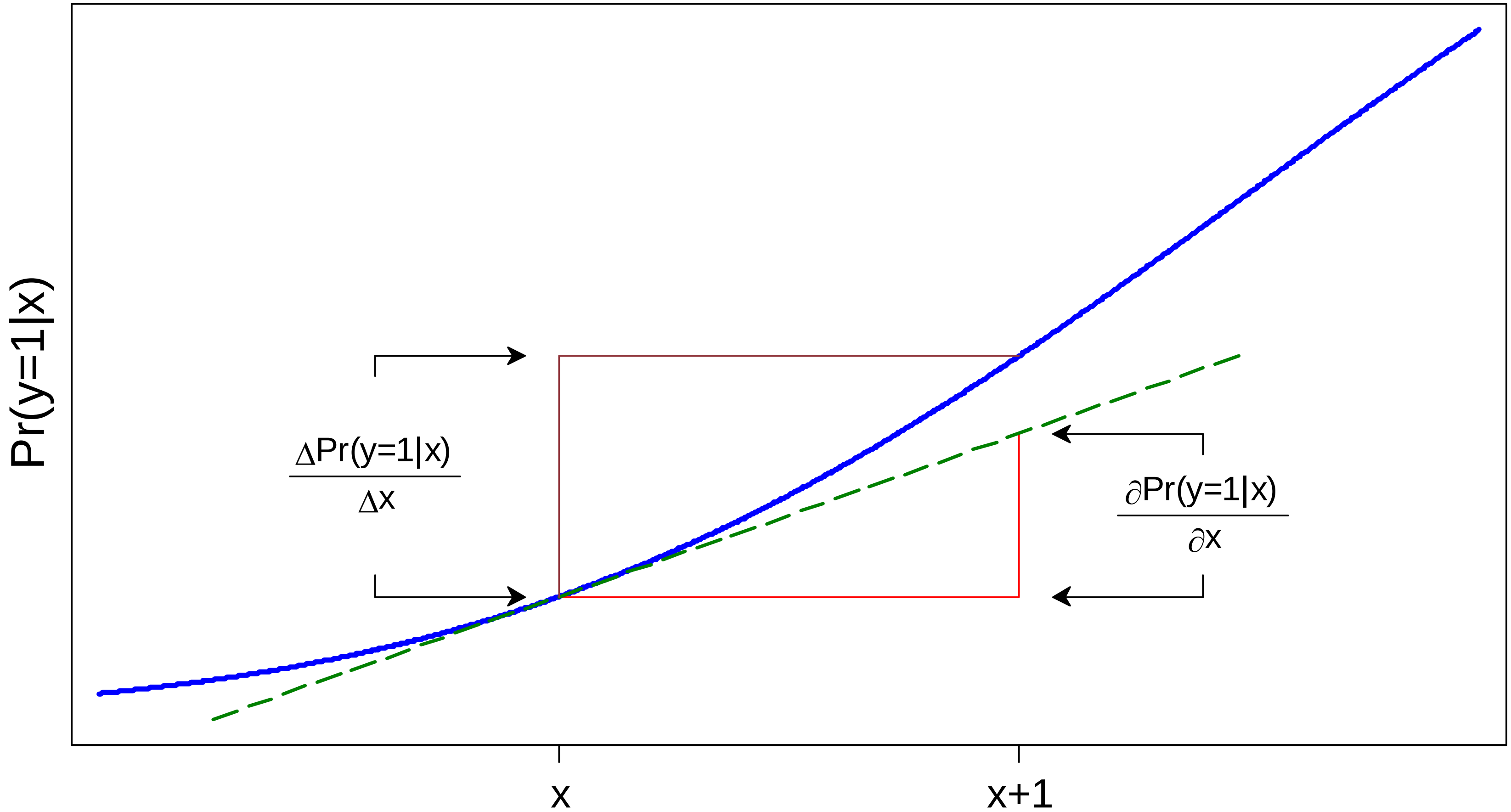
mtable: table making with discrete changes

```
. 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`: joint estimation over outcomes, not just looping.
2. `margins`: compact, table-like results.

Marginal effects



Mathematically, ...

Marginal change

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

Discrete change

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

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: results from dozen's of margins' estimates

```
. 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 from to 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
```

margins and lincom do the computations

```
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: multiple outcomes combined

```
. 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
```

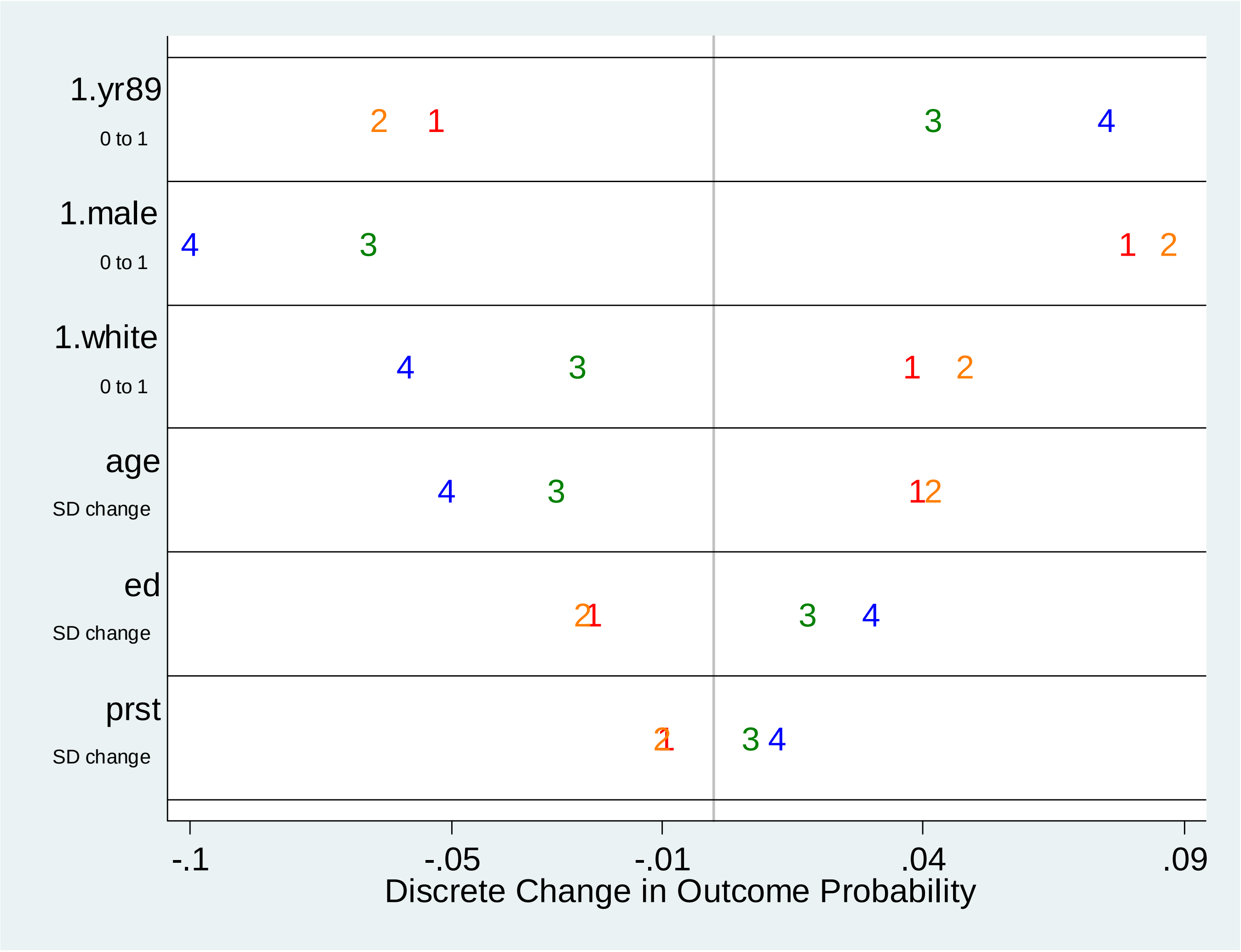
age				
+1 cntr	0.0023	0.0025	-0.0018	-0.0030
pvalue	0.0000	0.0000	0.0000	0.0000
+SD cntr	0.0387	0.0420	-0.0300	-0.0507
pvalue	0.0000	0.0000	0.0000	0.0000
Marginal	0.0023	0.0025	-0.0018	-0.0030
pvalue	0.0000	0.0000	0.0000	0.0000
ed				
+1 cntr	-0.0071	-0.0078	0.0056	0.0094
pvalue	0.0000	0.0000	0.0000	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.

To many numbers to absorb, so plot them…

dcplot: marginal effects plot (p-value can be added)

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



margins and lincom do the heavy lifting

```
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

Marginal effects have many advantages over standard logit output.

Is it time to re-evaluate standard output?

	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

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

AME

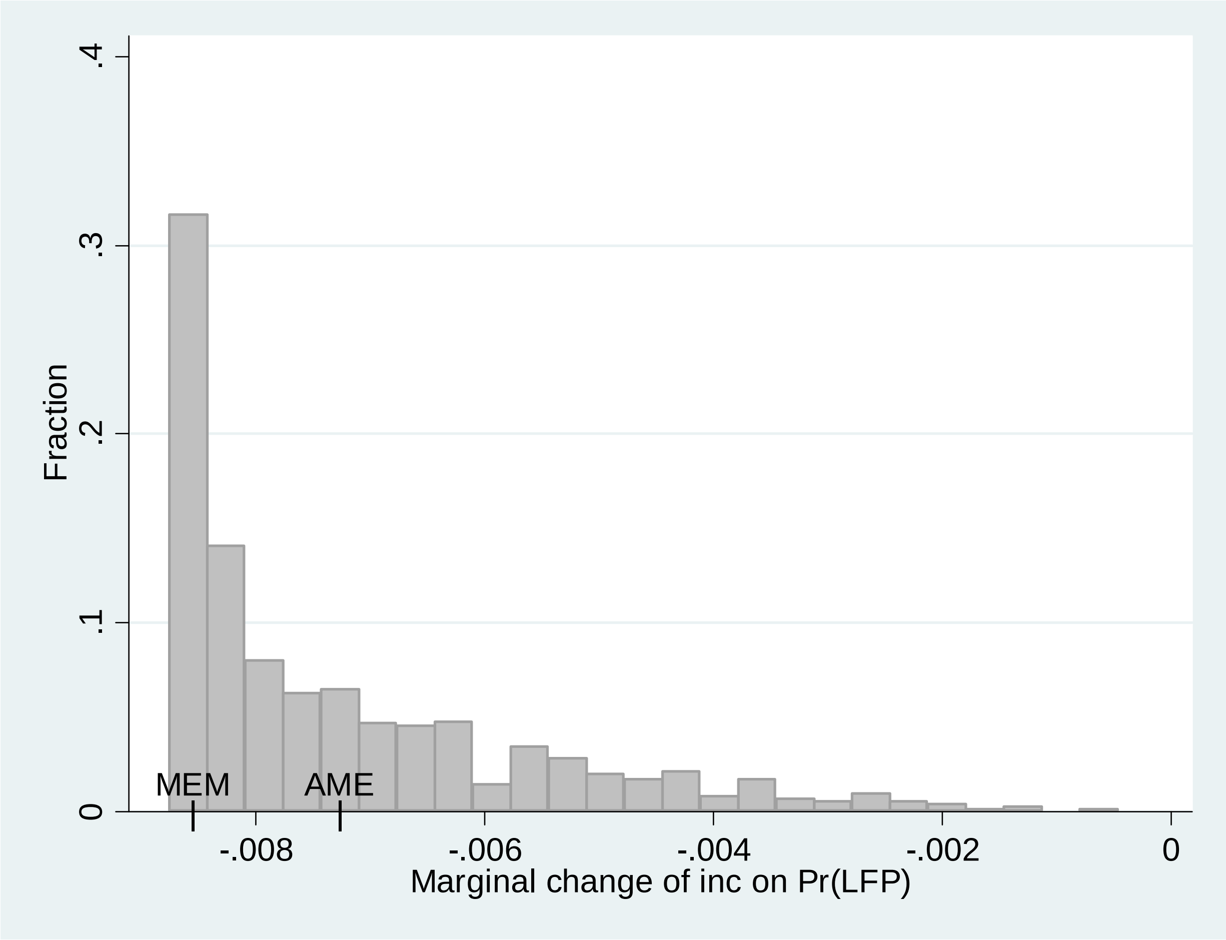
$$AMC = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Pr\left(y=1 \mid \mathbf{x}_i\right)}{\partial x_{ik}} \qquad ADC = \frac{1}{N}\sum_{i=1}^{N}\frac{\Delta \Pr\left(y=1 \mid \mathbf{x}_i\right)}{\Delta x_{ik}}$$

Should you replace one mean with another?

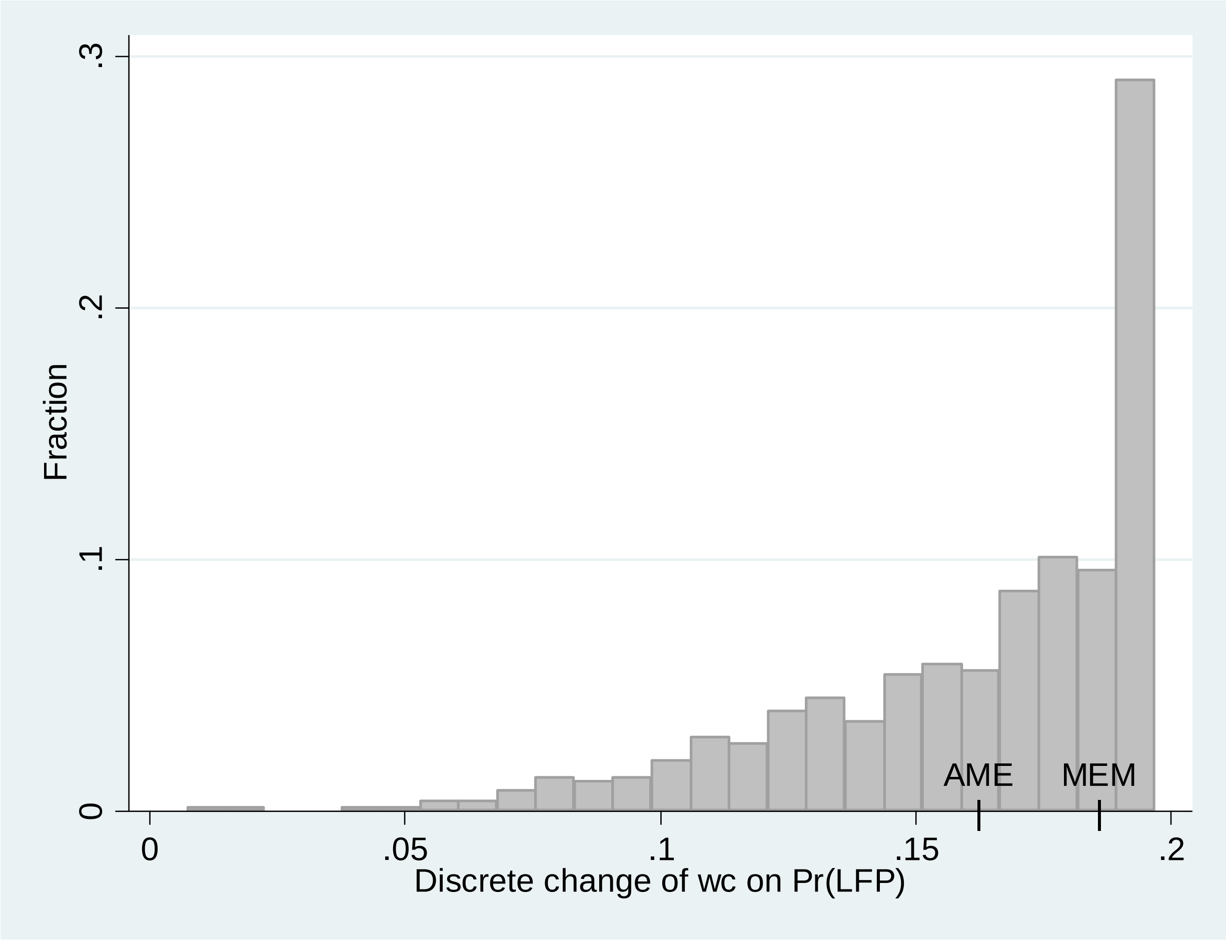
- What is the question you are trying to answer?
- Maddala's 1980 advice was pretty good, but his insights forgotten.
- The distribution of effects is important, but <u>largely</u> overlooked.

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

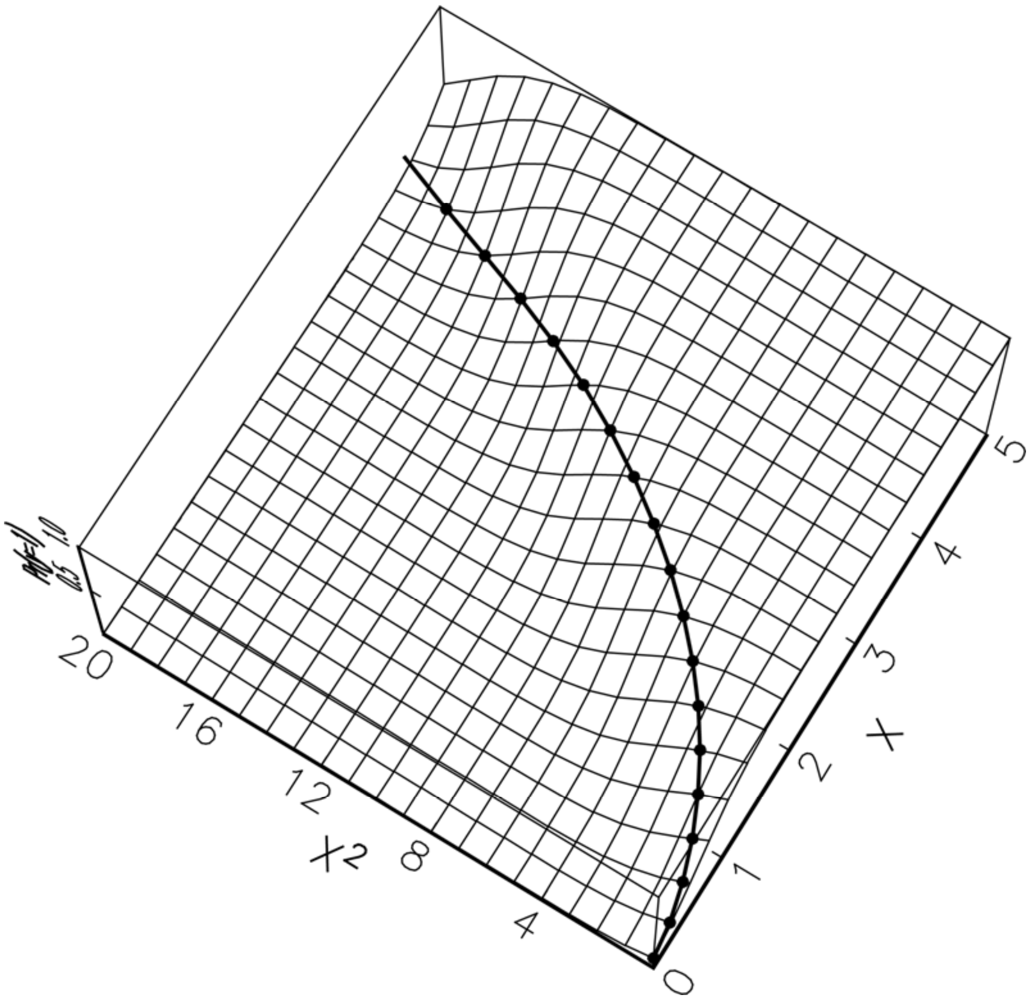
Linked marginal effects

1. "Strongly linked" variables which are handled elegantly by factor variables.

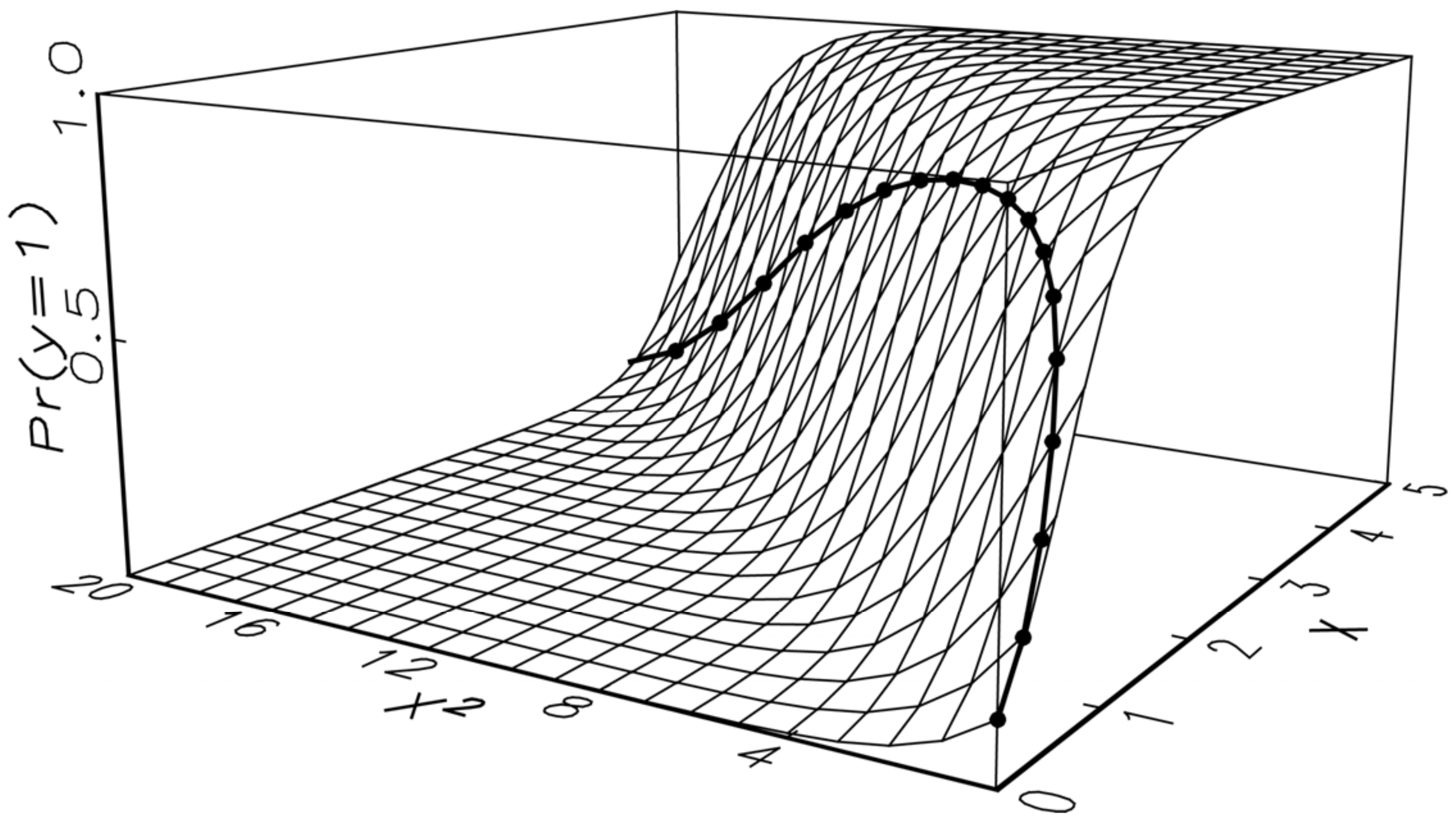
2. "Weakly linked" variables can be handed with **`at(x=gen())`**

Start with strongly linked variables...

Age and age-squared are strongly linked



Leading to



- A marginal effect of x automatically adjusts for x-squared.
- Does this make sense for weakly linked variables?

Height and weight are weakly linked

Modeling arthritis

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

The question

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

The problem

1. Height and weight are correlated about .5.

2. Increasing height, holding weight constant is not the question since it changes the BMI.

3. Allow height to increase and let weight increase a corresponding amount.

   - This type of problem has many applications when multiple indicators are used.

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 & 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: simplify specification and build tables

```
. 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
```

Global and local means

1. **As observed** and **at means** are part of a continuum.
2. When changing a variable to make predictions, there are limitations with:
   a. Holding other variables at the mean.
   b. Keeping other variables at their observed values.
3. Local means deals with being **off the support** with using **`atmeans`**.

Global means: the foundation of spost9!

```
. 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

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
```

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
```

Predictions with local means

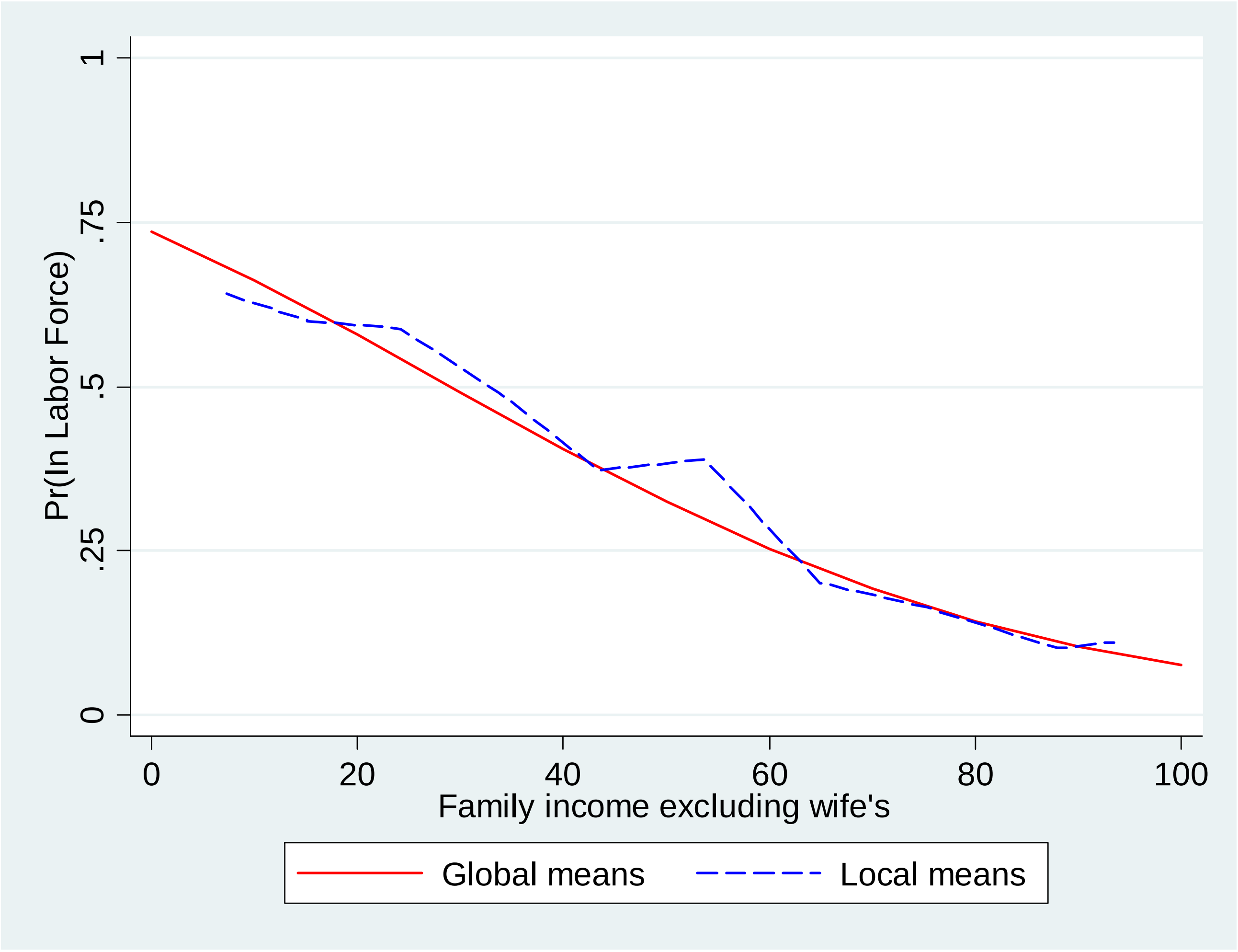
```
. qui mtable, over(k5) at(wc=1) estname(College) atmeans ///
>             atvars(_none) right
. mtable, over(k5) dydx(wc) estname(Diff) atmeans stats(est p) ///
>             atvars(_none) names(columns) right

      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
```

Comparing the results...

Comparing global and local means

k5	Global - Local			Global			Local		
	NoCol	Col	Diff	NoCol	Col	Diff	NoCol	Col	Diff
0	-0.02	-0.02	0.01	0.60	0.77	0.17	0.58	0.76	0.17
1	0.06	0.07	0.01	0.27	0.46	0.18	0.34	0.53	0.19
2	0.07	0.11	0.05	0.09	0.17	0.09	0.15	0.29	0.13
3	-0.01	-0.01	-0.01	0.02	0.05	0.03	0.02	0.04	0.02

Plots with global and local means



If time permits...

Predictions with global means

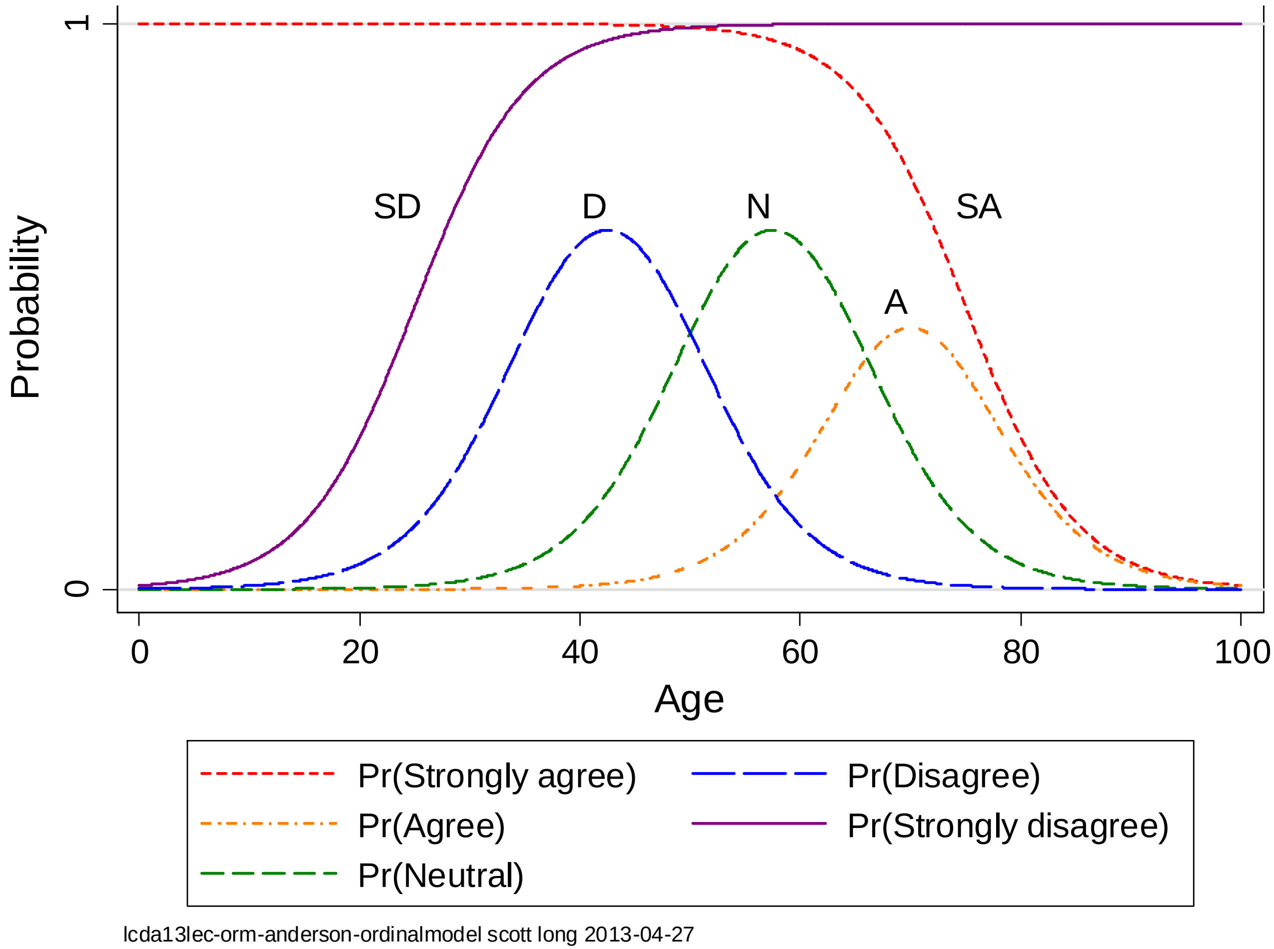
```
. sysuse binlfp4, clear
. logit lfp k5 k618 i.agecat i.wc i.hc lwg inc, nolog

. 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"
```

Beyond the parameters

Ordinal models are very restrictive



Party identification

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

     party5 |      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
```

OLM: Parallel regression assumption

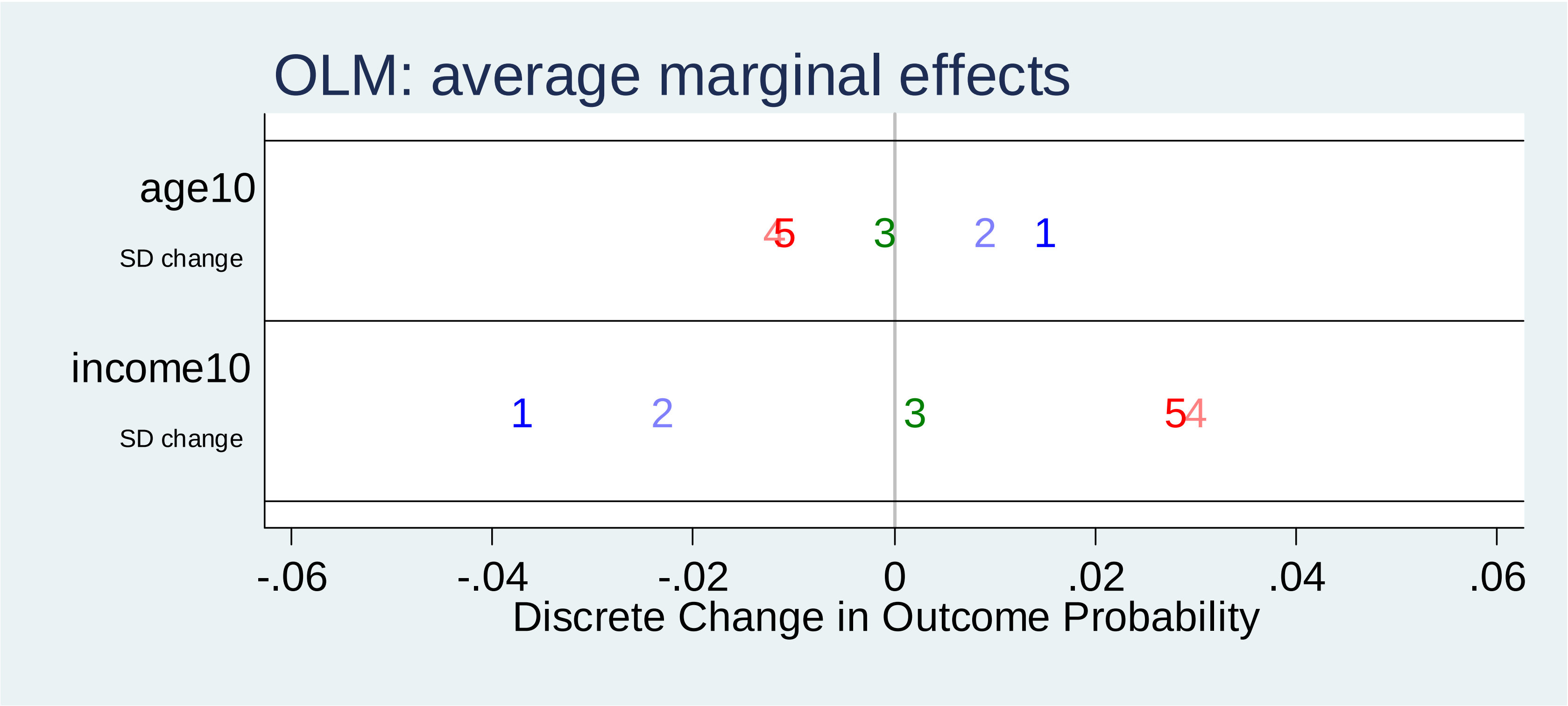
```
. brant

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).

OLM: AME

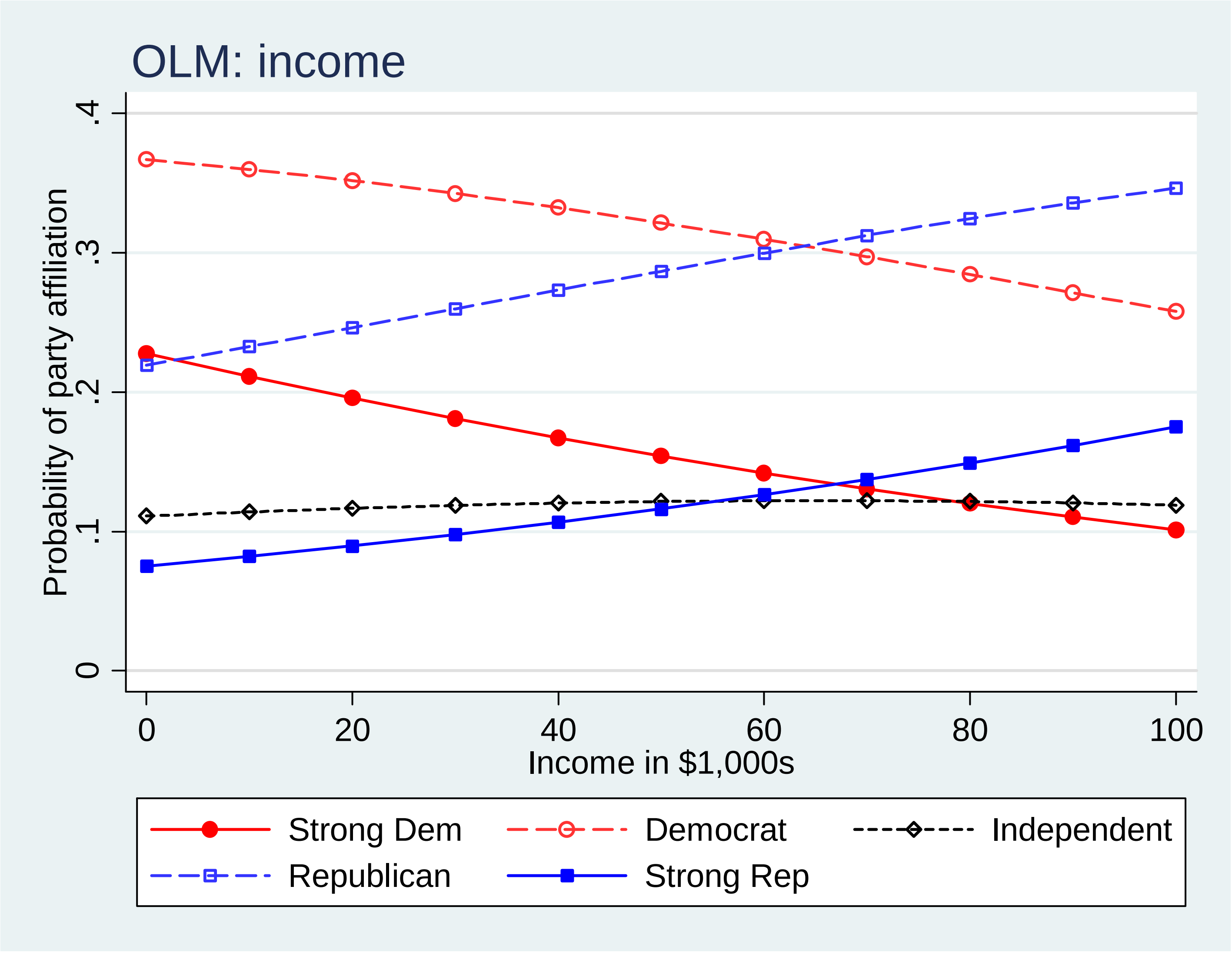
```
mchange
dcplot age10 income10, ...
```



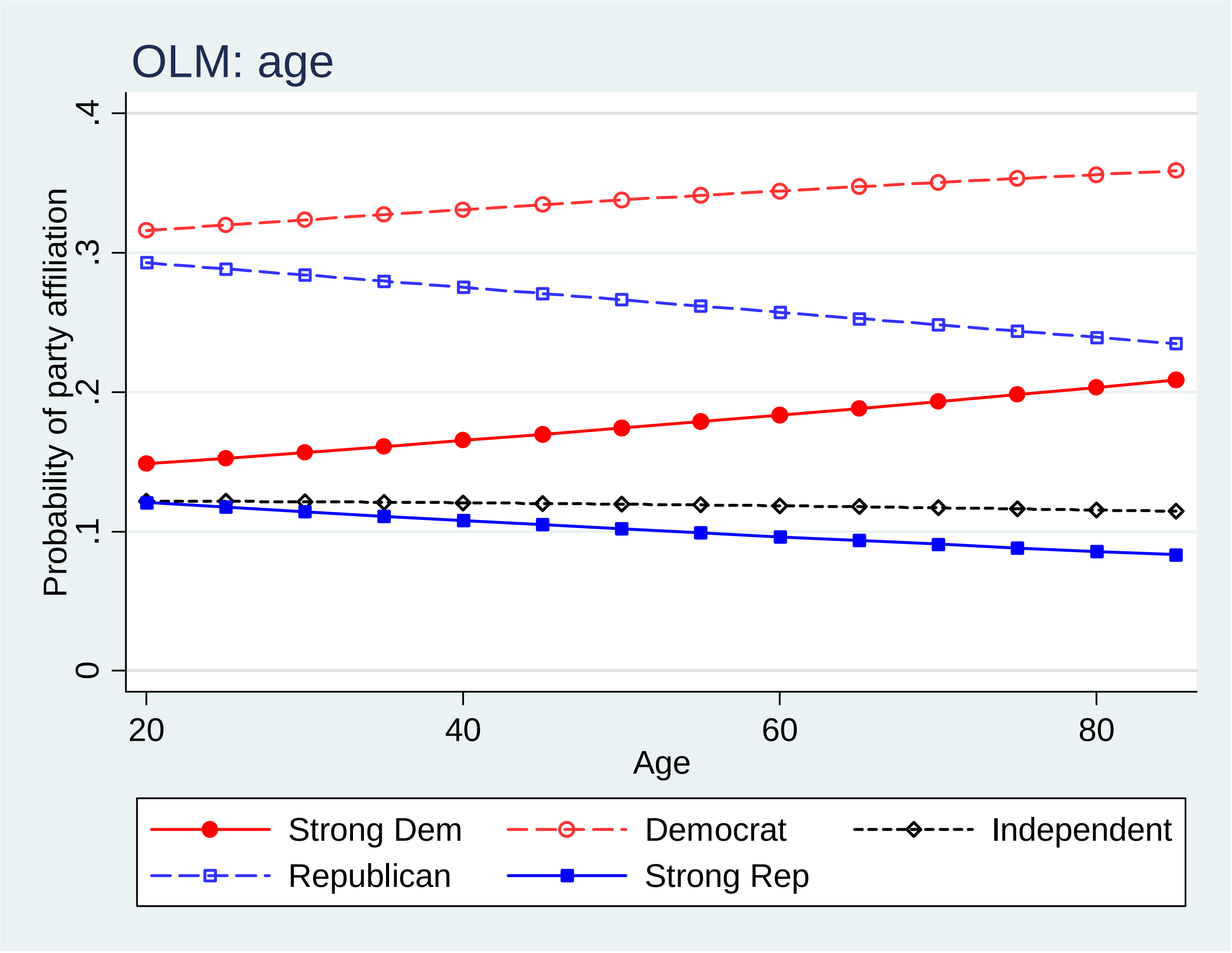
OLM: Probabilities to plot

```
. mgen, atmeans at(`at_age') stub(olmage)

Variables computed by: margins, at(age10=(2(.5)8.5)) atmeans

Variable      Obs Unique      Mean       Min       Max  Label
------------------------------------------------------------------
olmagepr1      14     14  .1773212  .1484803  .2086263  pr(y=1_SD)..
olmagell1      14     14  .1496142  .1213707  .1628012  95% lower...
olmageul1      14     14  .2050282  .1755899  .2544515  95% upper...
olmageage10    14     14      5.25         2       8.5  Age in dec..
olmageCpr1     14     14  .1773212  .1484803  .2086263  pr(y=1_SD)
olmagepr2      14     14   .338745   .316049  .3587669  pr(y=2_D)

:::snip:::

olmageCpr4     14     14  .8989504  .8792652  .9167384  pr(y<=4_R)..
olmagepr5      14     14  .1010496  .0832616  .1207348  pr(y=5_SR)..
olmagell5      14     14   .082297  .0605158  .0968657  95% lower ..
olmageul5      14     14  .1198021  .1060074   .144604  95% upper ..
olmageCpr5     14      2         1  .9999999         1  pr(y<=5_SR).
-------------------------------------------------------------------

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

OLM: ologit by income



OLM: ologit by age



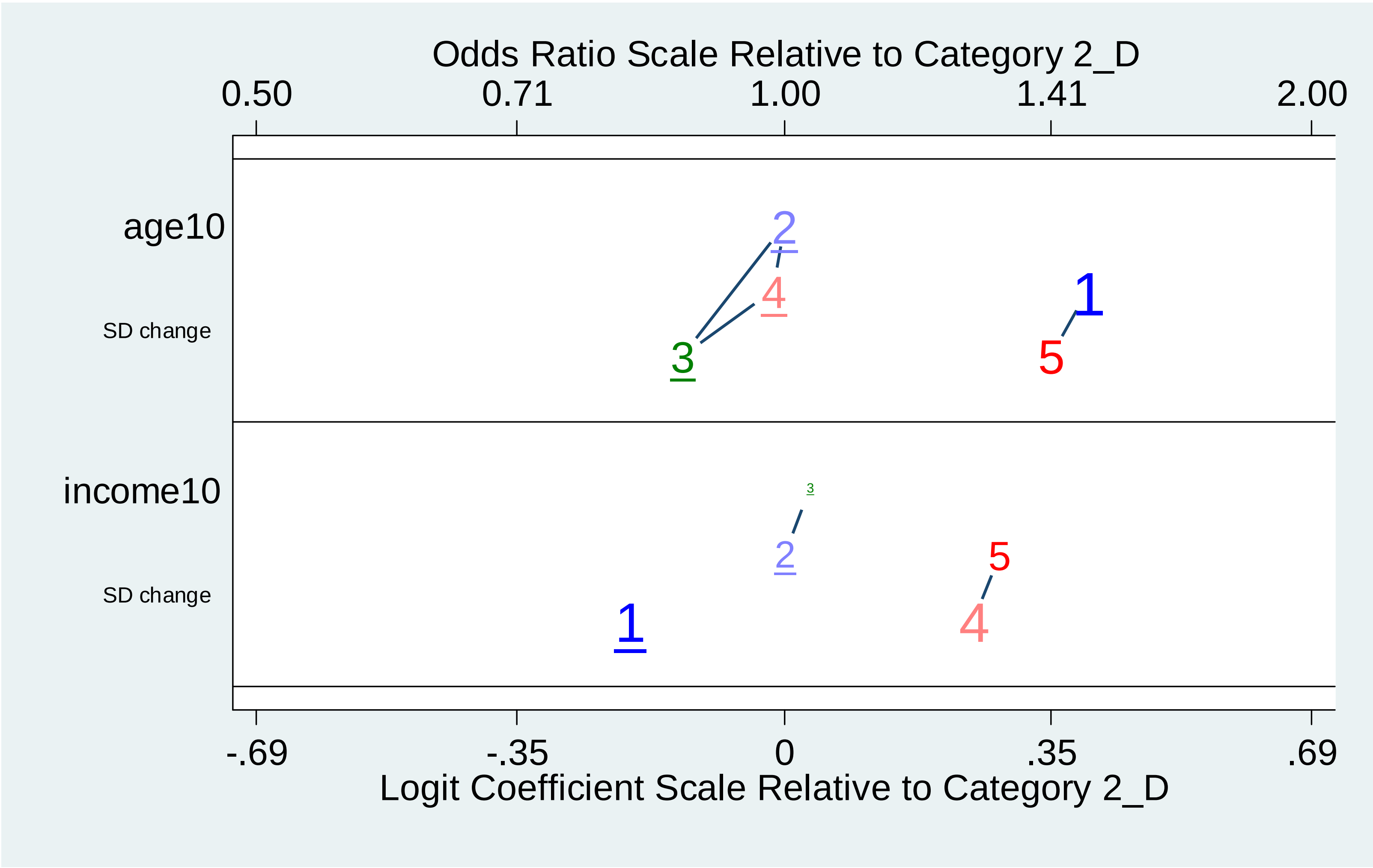
mlogit of partyid

```
. 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)
:::snip:::

. mchange
. orplot, dc mcolors(`partycolor') ...
```

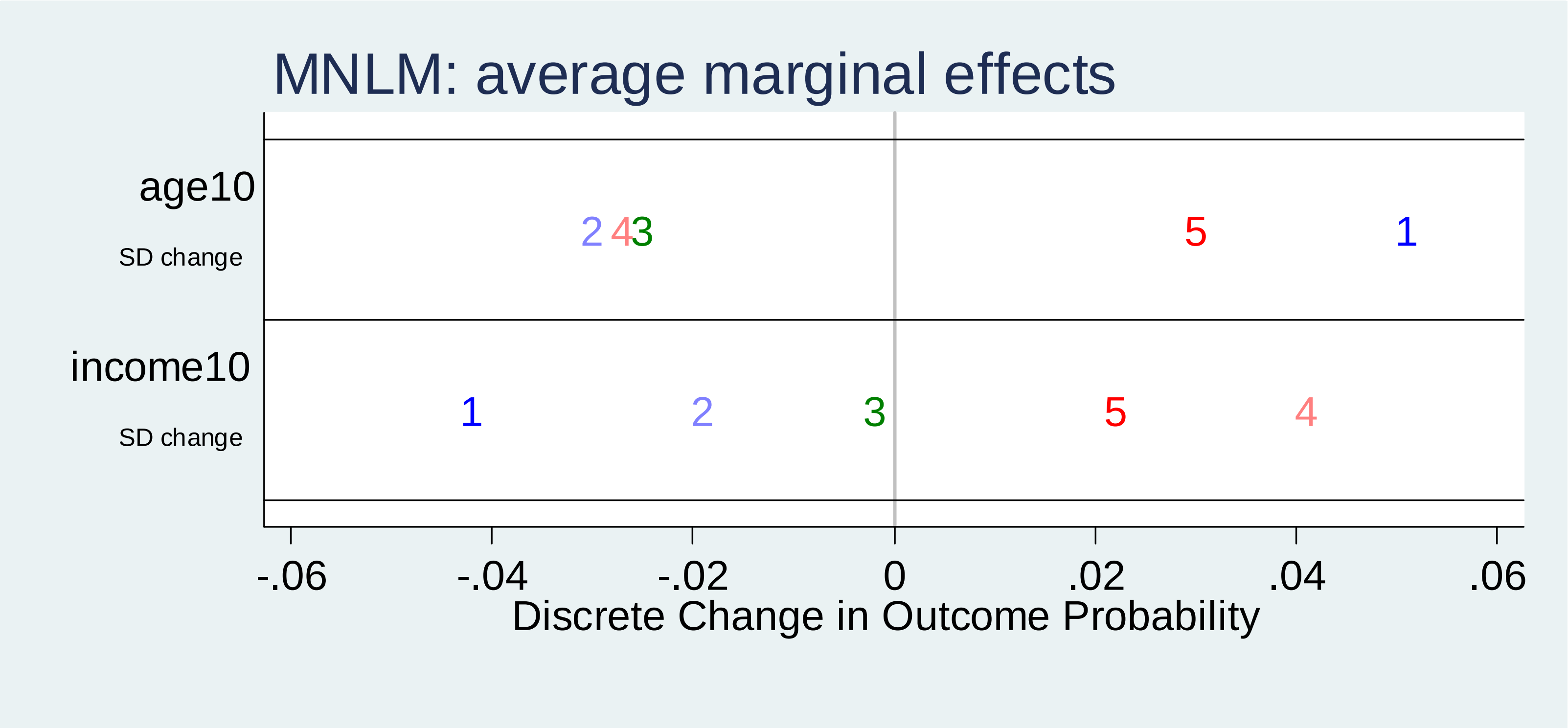
MNLM: mlogit odds ratio plot with ame's

```
orplot age10 income10, dc
```



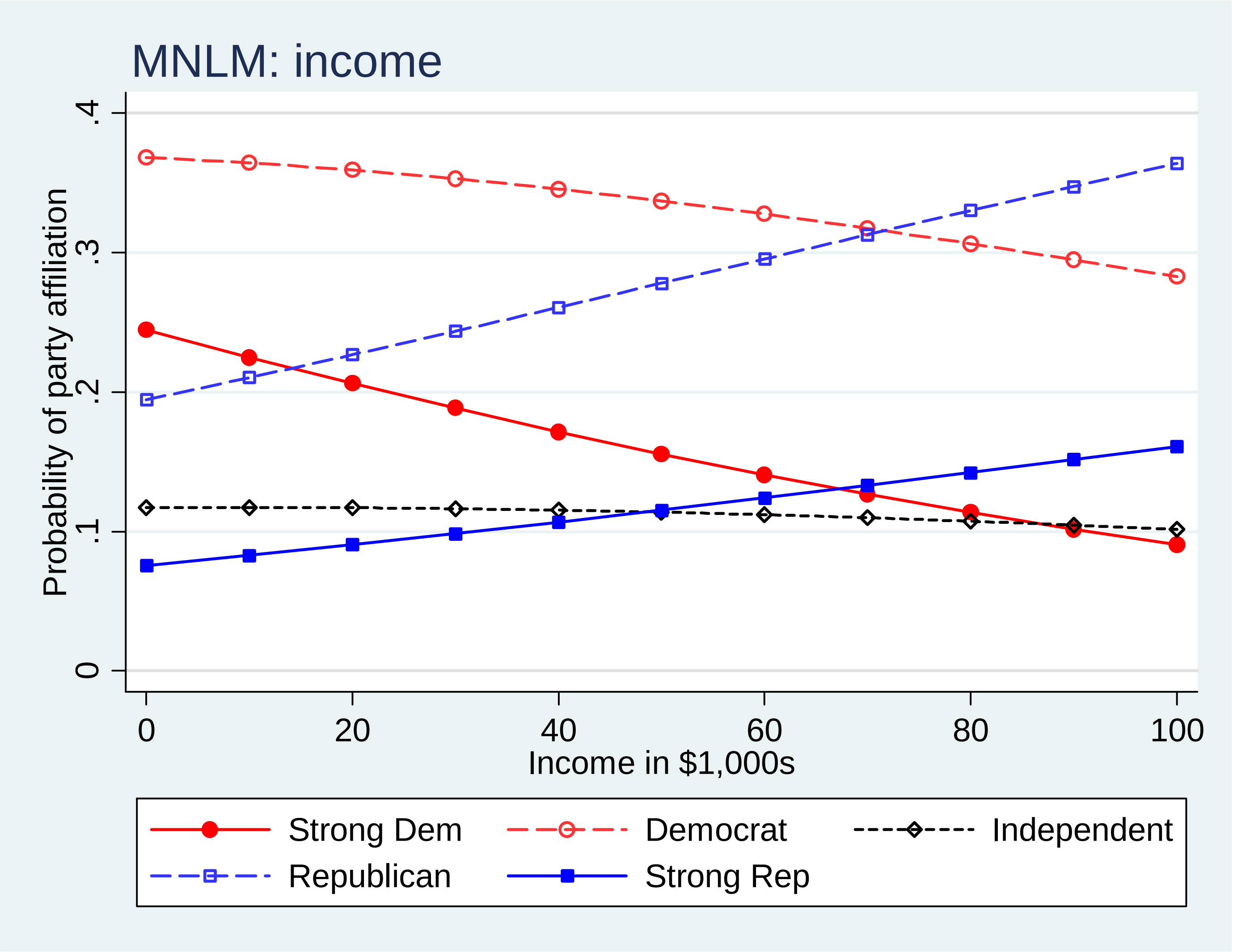
MNLM: mlogit AME

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

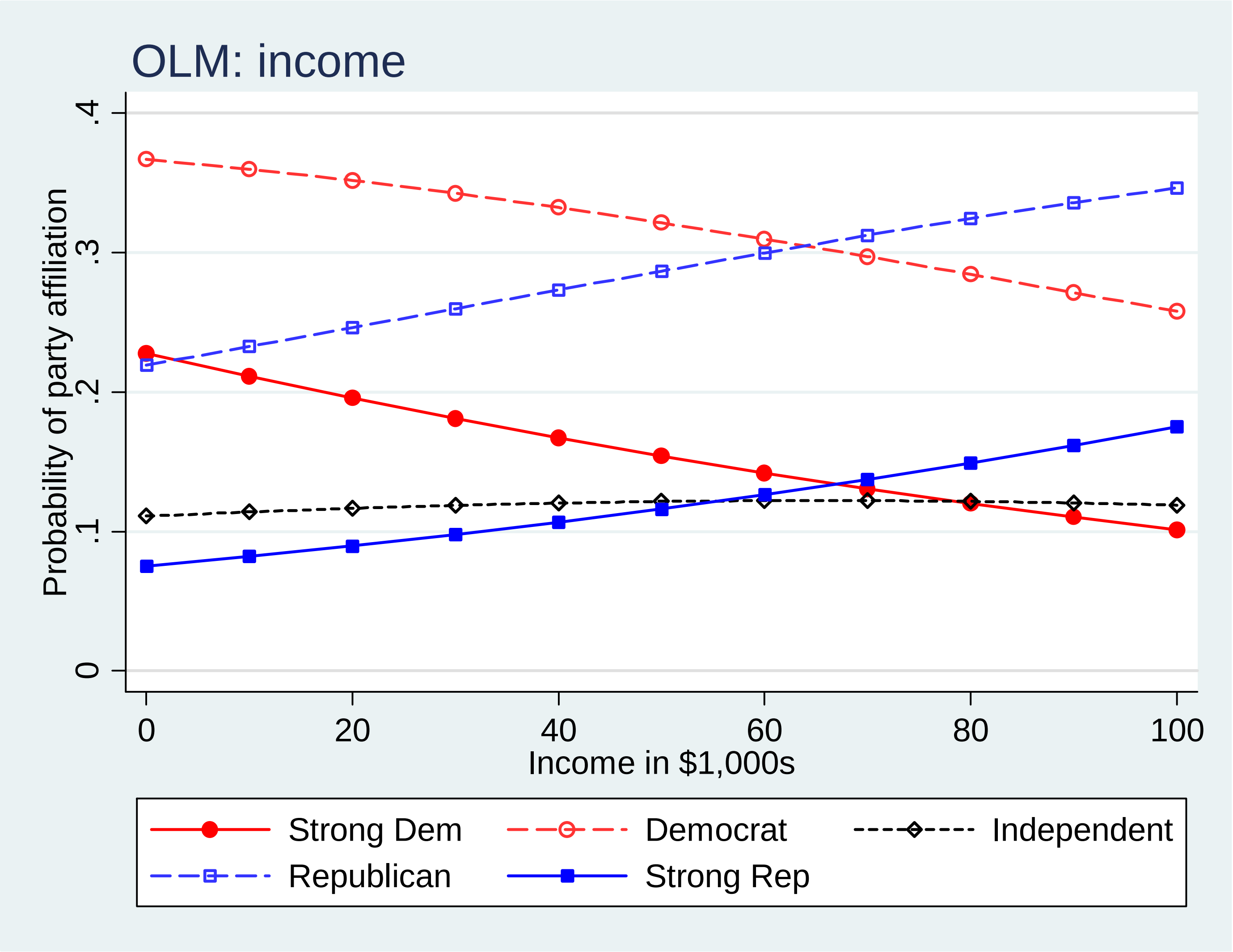


What happened with 1 and 5?

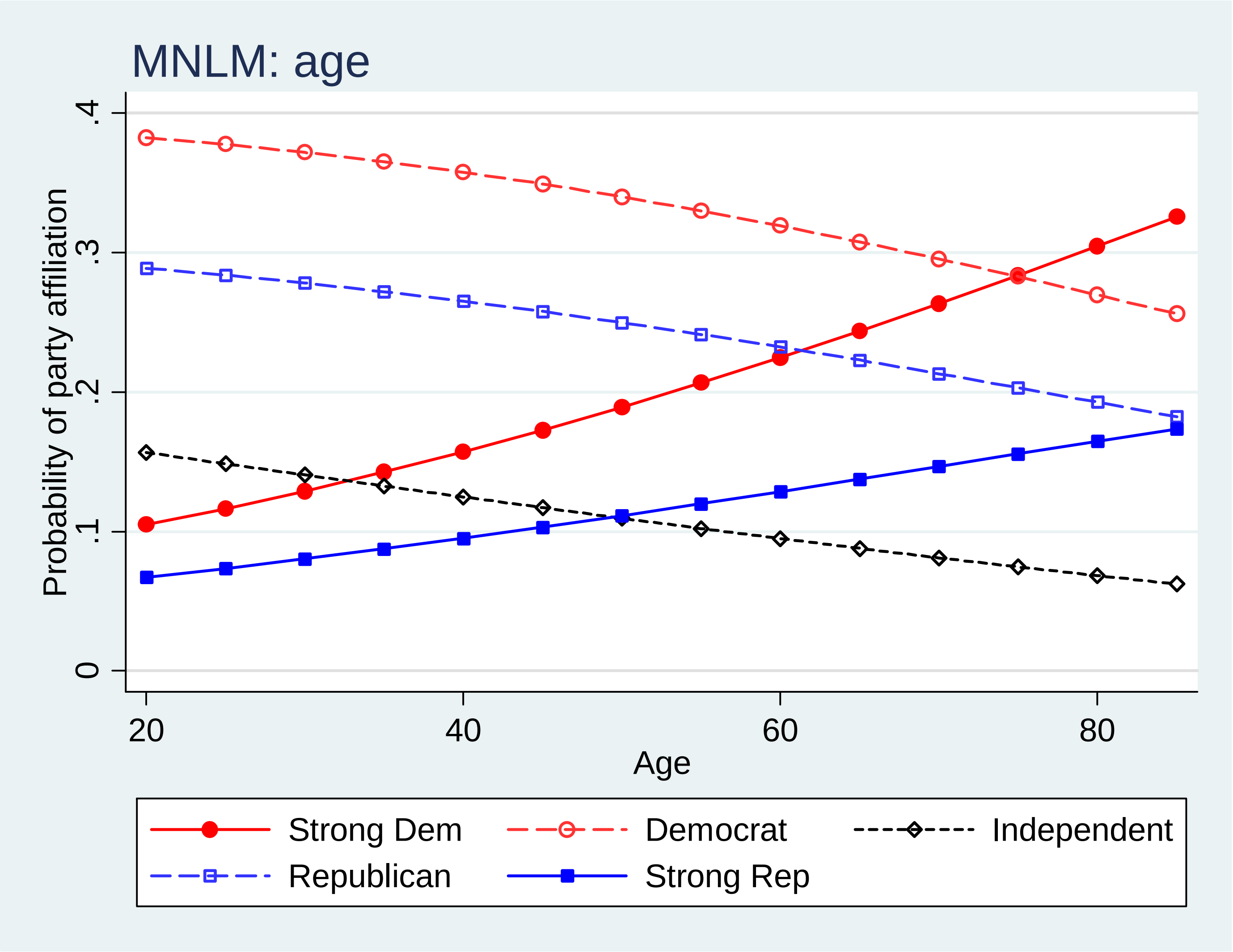
MNLM: mlogit by income



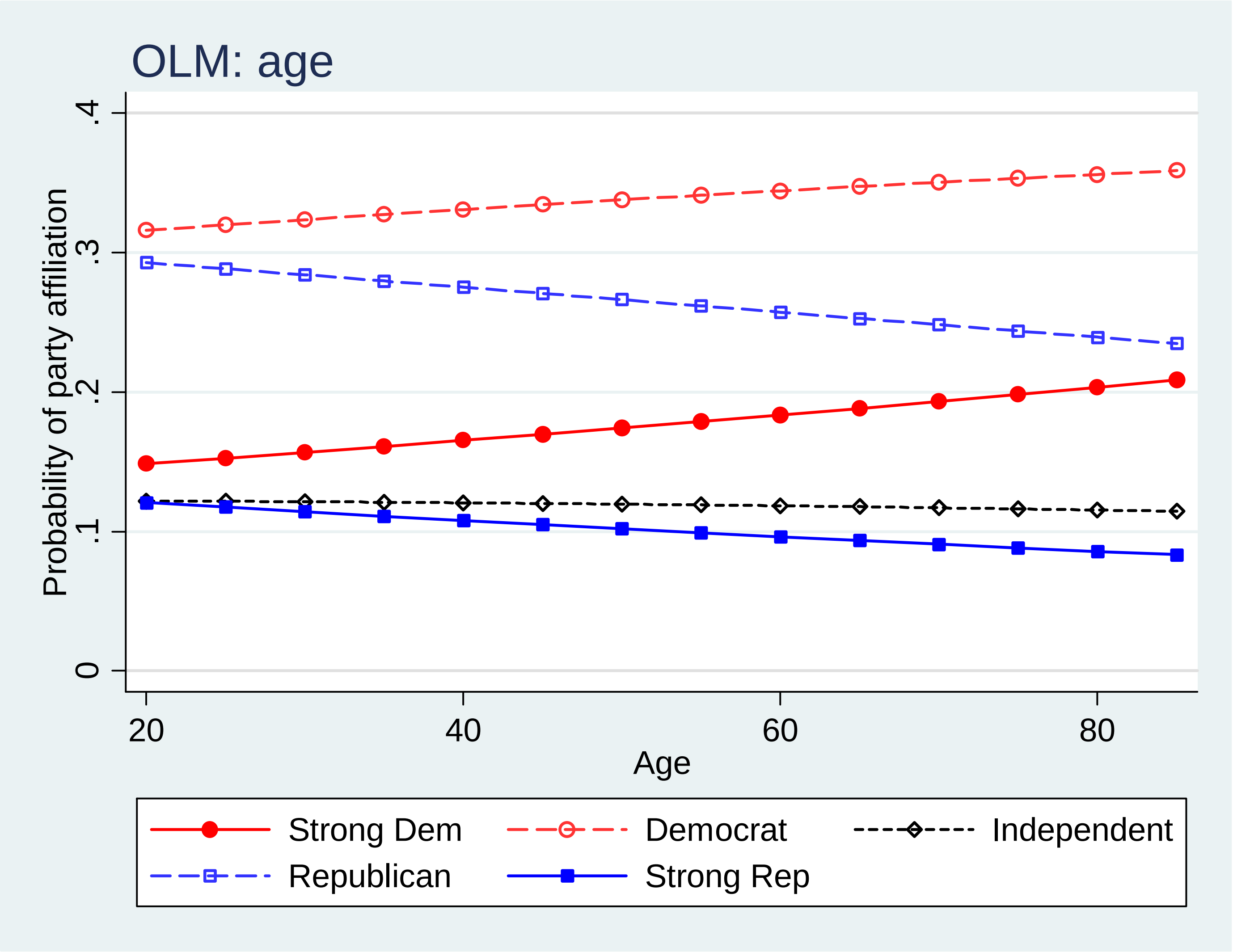
OLM: ologit by income



MNLM: mlogit by age



OLM: ologit by age



Post-estimation test & fit

brant: parallel regression test

Shown above.

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 for 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 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
```

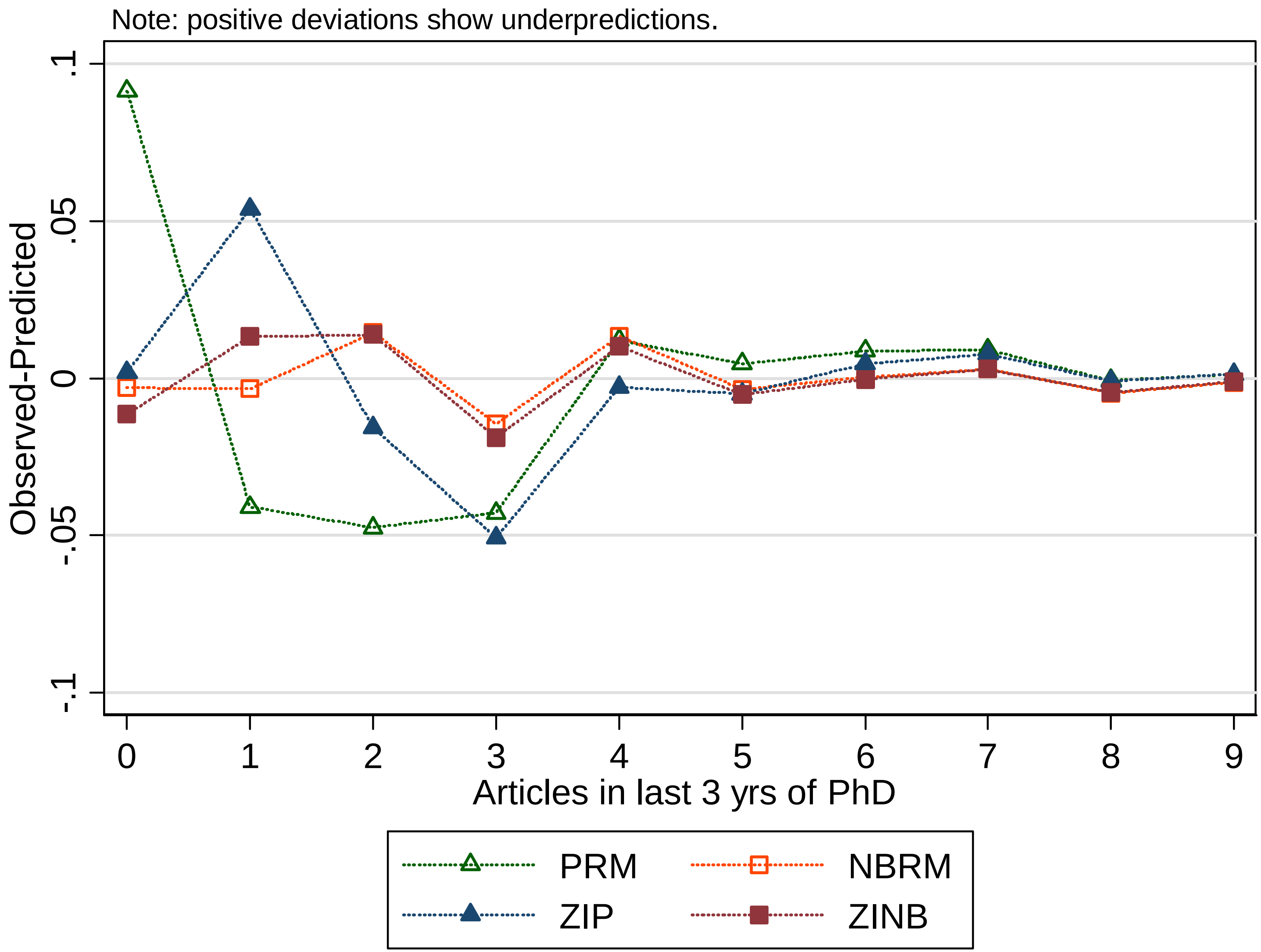
And so on for all models…

Comparison of Mean Observed and Predicted Count

Model	Maximum Difference	At Value	Mean |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


Note: positive deviations show underpredictions.
Observed-Predicted
.1
.05
0
-.05
-.1
0
1
2
3
4
5
6
7
8
9
Articles in last 3 yrs of PhD
PRM
NBRM
ZIP
ZINB

```
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 predictions for individual observations.
4. Let **`predict`** predict everything that **`margins`** can estimate
5. **`at(x=gen(x+sd(x))`**: **`egen()`** for **`at()`**
6. **`autopost`**: automatically save current estimation command if it is in memory; if not in memory, load the one that was autoposted.
7. Better ways to incorporate local means?

Data analysis

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

Useful things that seem easy

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

Programming

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

Graphics

1. 3d wireframe graphics

Move the best functions of SPost into Stata

In general, user written commands challenge reproducible results.

Stata and reproducible results

How can Stata change to support this movement.

Thank you

1. For the files, `findit scottlong` and follow the links.
2. In Stata, run `spost13update`

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