

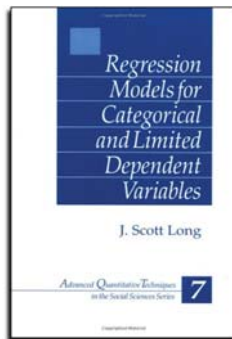
Interpreting regression models using Stata

Scott Long

August 13, 2013

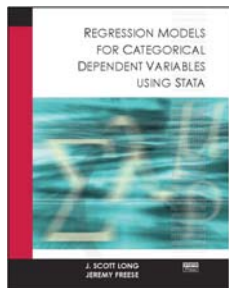
Long-StataCorp-2013-08-11.docx

Interpreting regression models



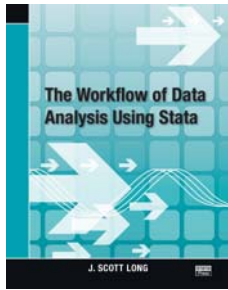
- 1980s Interpreting log-linear and multinomial models to support substantive research
- 1991 *Markov: A Statistical Environment for GAUSS*
- 1996 change.ado and genpred.ado in Stata 4
- 1997 *Regression Models for Categorical and Limited Dependent Variables*
- 1997 *Markov 2.5*, ineffectively supporting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

Working with StataCorp



- 1998 Bill Sibney 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

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Stata at Indiana

My students appeared in class wearing...



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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"

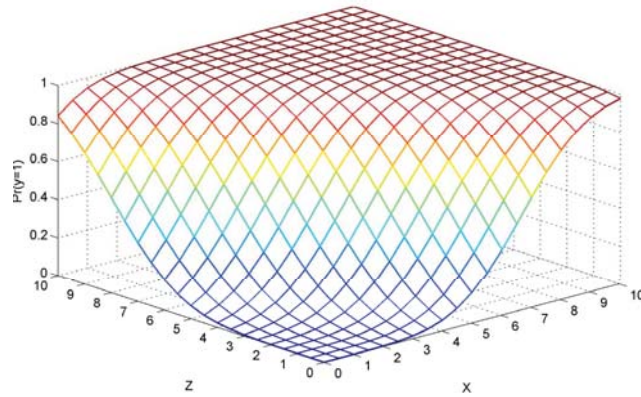
Other SPost13 commands

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

Things I (we) would like to see in Stata

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Interpretation using predictions



With multiple outcomes and K predictors...

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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.

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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.

mllincom: tables of linear combinations (wrapper for **lincom**)

Why aren't margins and marginsplot and sufficient?

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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:::
```

	Margin	Delta-method 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

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

Other statistics could be included in the table.

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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

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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?

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margins

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

Adjusted predictions
Model VCE : OIM
Number of obs = 2293

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

l._at : yr89 = 0
:::snip::

	Margin	Delta-method 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

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Adjusted predictions
Model VCE : OIM
Number of obs = 2293

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

l._at : yr89 = 0
:::snip::

	Margin	Delta-method 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::

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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	prst
0.877	44.935	0.341	0.196	0.171 39.585

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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)
```

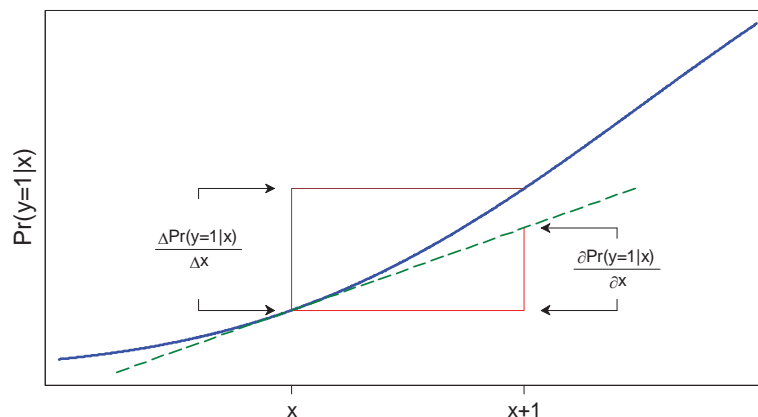
	1 SD	2 D	3 A	4 SA

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

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

Marginal effects



Mathematically, ...

Marginal change

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

Discrete change

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

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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

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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.

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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

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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
```

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```
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
```

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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

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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

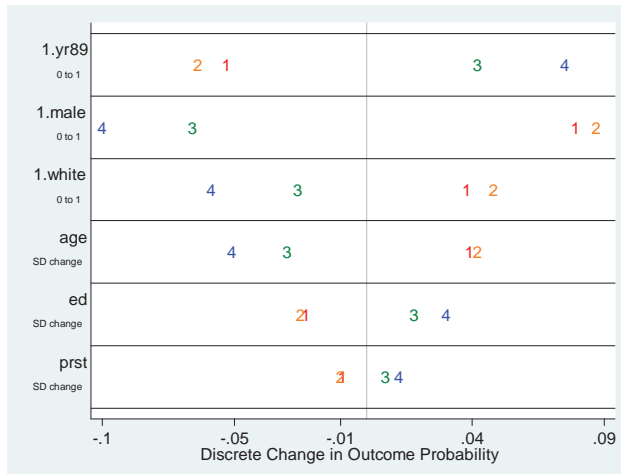
1: Predictions averaged over the sample.

To many numbers to absorb, so plot them...

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

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



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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]
}

```

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```

  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'))
}

```

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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		

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AME and MEM

A sometimes less than fruitful debate...

MEM

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

AME

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

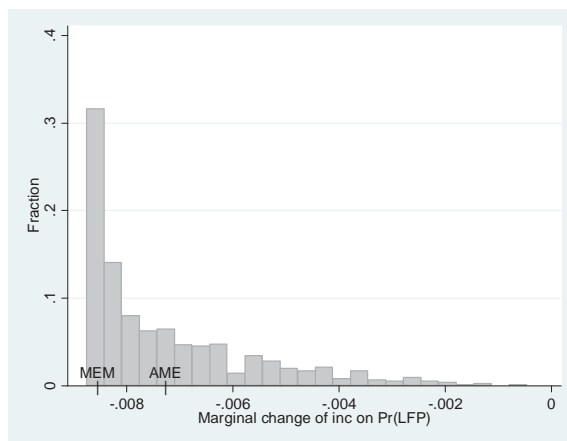
Should you replace one mean with another?

- 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 largely overlooked.

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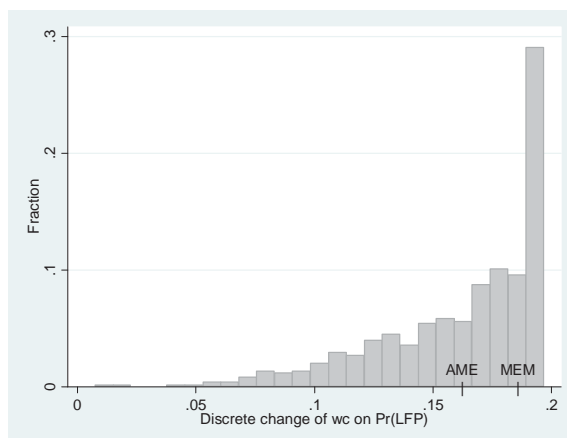
Distribution of ME's

Marginal change for income



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Discrete change for woman attending college



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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.

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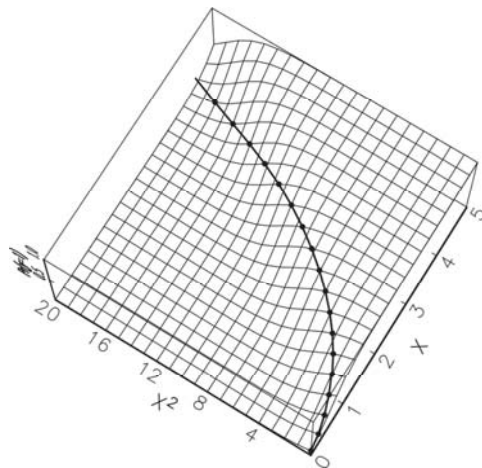
Linked marginal effects

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...

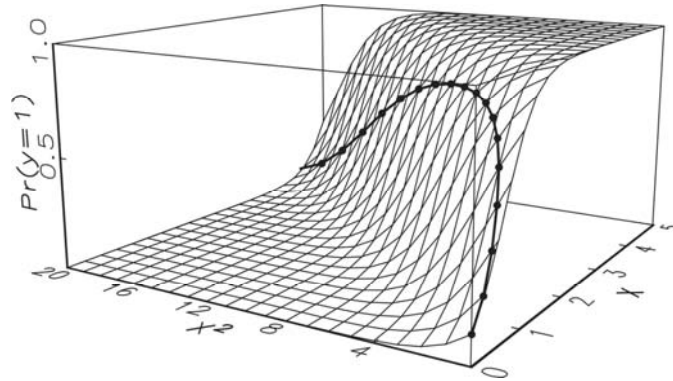
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Age and age-squared are strongly linked



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Leading to



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

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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.

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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 = e1(r(sd),1,1)
. estimates restore lgt
```

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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

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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_difference	0.051	0.000	0.046	0.056

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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**.

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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

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

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Local means

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

Expression: Pr(lfp)

	1. wc	k5	k618	2. agecat	3. agecat	1. 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

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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...

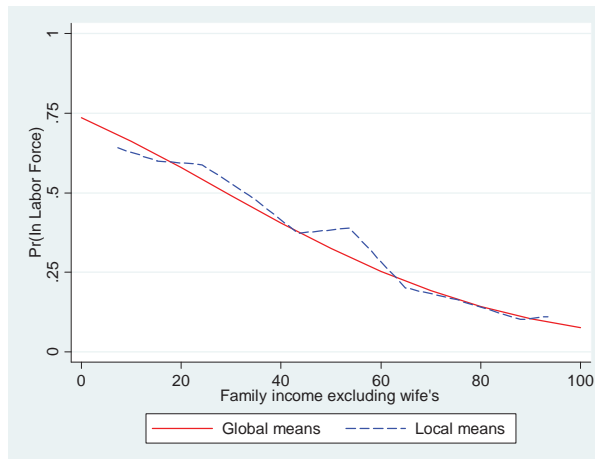
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Comparing global and local means

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

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Plots with global and local means



If time permits...

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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...

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Predictions with local means

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

Expression: Pr(lfp)

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

		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

```

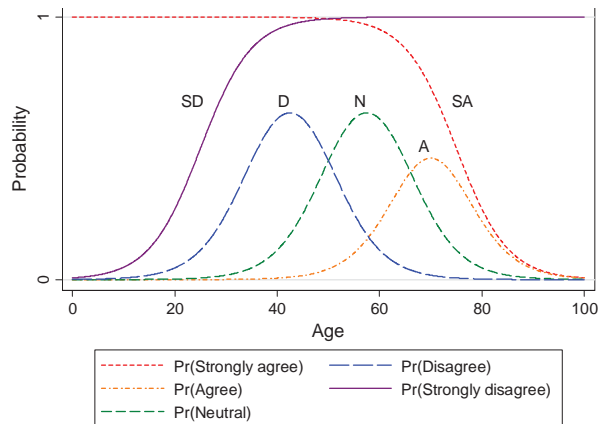
:::snip::
. matrix tab = r(table)
. matrix tab = tab[1...,8..11]
. matrix colnames tab = local_inc local_pr local_ll local_ul
. svmat tab, names(col)
. label var local_pr "Local means"
. label var local_ll "95% lower limit"
. label var local_ul "95% upper limit"
. label var local_inc "Family income excluding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

```

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Beyond the parameters

Ordinal models are very restrictive



lcal13lec-orm-anderson-ordinalmodel scott long 2013-04-27

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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

```

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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

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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.

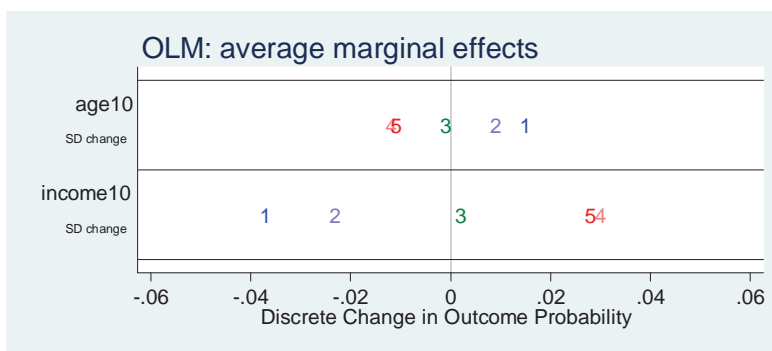
SUGGESTION

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

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OLM: AME

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



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OLM: Probabilities to plot

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

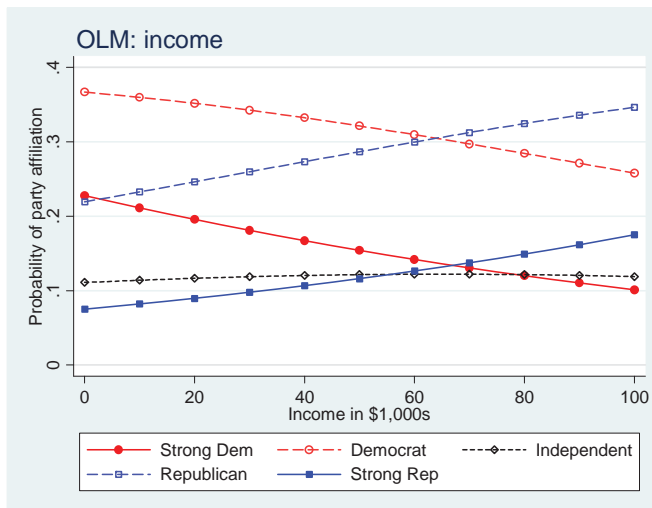
Variables computed by: margins, at(age10=(2(.5)8.5)) atmeans

Variable	Obs	Unique	Mean	Min	Max	Label
olmagepr1	14	14	.1773212	.1484803	.2086263	pr(y=1_SD)..
olmage1l1	14	14	.1496142	.1213707	.1628012	95% lower...
olmageu1l	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)..
olmage1l5	14	14	.082297	.0605158	.0968657	95% lower ..
olmageu15	14	14	.1198021	.1060074	.144604	95% upper ..
olmageCpr5	14	2	1	.9999999	1	pr(y<=5_SR).

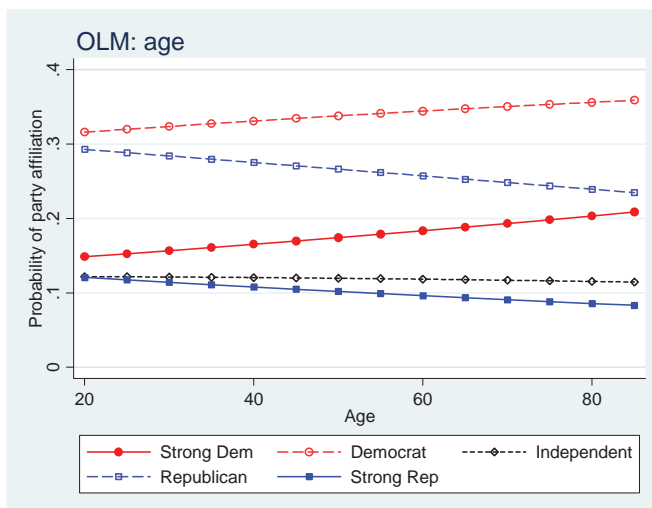
```
. mgen, atmeans at(`at_inc`) stub(olminc)
```

```
::: 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

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```
. 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)

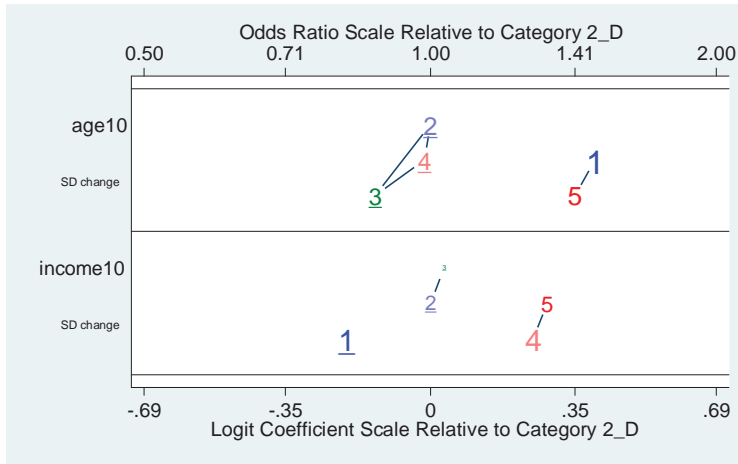
```
:::snip:::
```

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

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MNLM: mlogit odds ratio plot with ame's

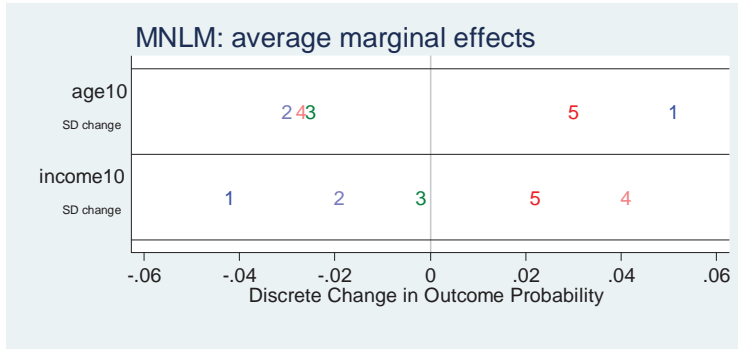
```
orplot age10 income10, dc
```



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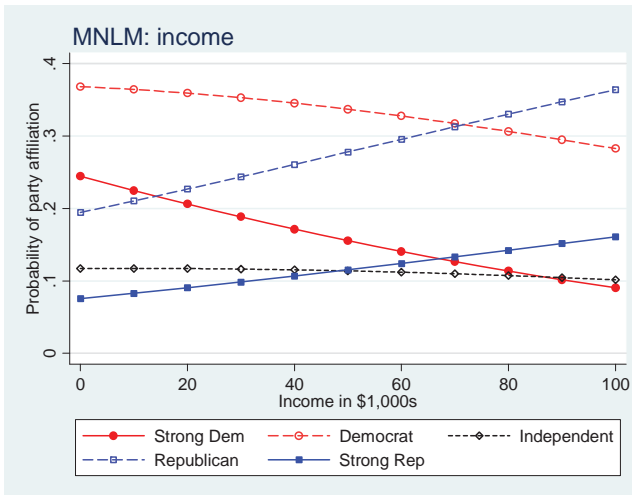
MNLM: mlogit AME

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

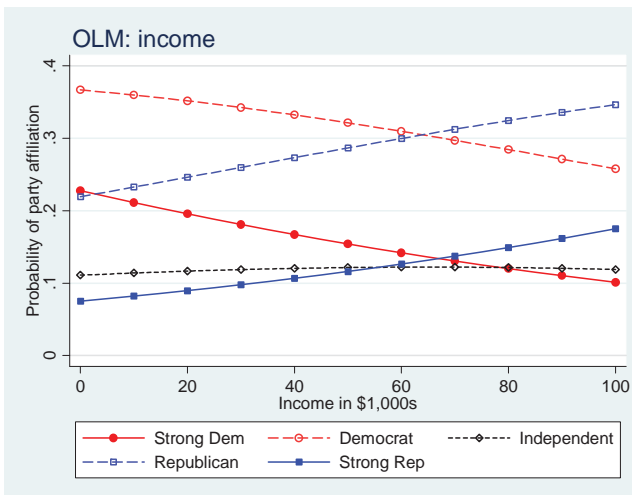


What happened with 1 and 5?

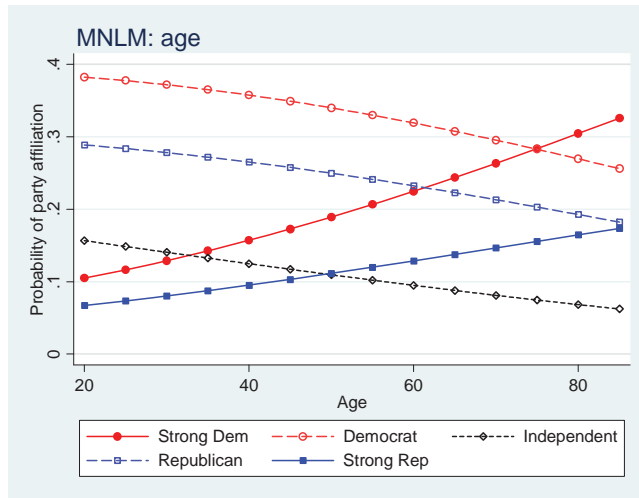
MNLM: mlogit by income



OLM: ologit by income

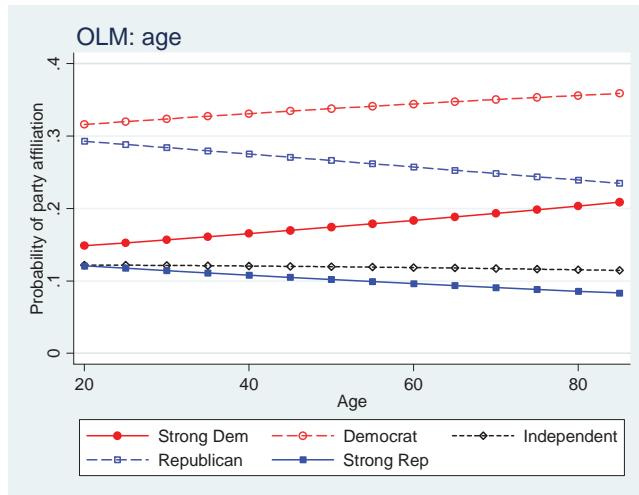


MNLM: mlogit by age



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OLM: ologit by age



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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...

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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

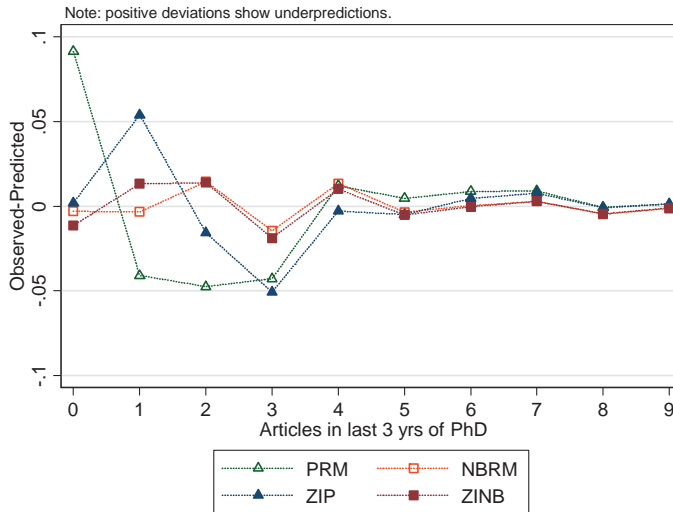
And so on for all models...

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



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

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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.

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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

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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

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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?

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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

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Programming

1. Better tools for factor variables (or let Jeff make house calls)
 - o 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.

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Thank you

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

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