Quantitative Data Analysis II

SOC 781

O/logit review &

Nominal outcomes: mlogit intro

Today we will…

- Logit & ologit questions/concerns
- Multinomial logistic intro

Logit & ologit questions

- Don’t get too wrapped up in the intricacies
  - or overwhelmed with forthcoming details

- Focus on basics and application of techniques
  - usefulness for interpretation

- If you pick up what I’m putting down, great
- If not, soak in what you can and ask questions

- For our purposes it’s more important to be able to understand how to drive the car than to understand exactly what’s going on under the hood

Logit & ologit questions

What is the value of odds ratios from o/logit?

- Indeed, odds ratios are not intuitive since they are only relative
  - but they provide a constant effect

- Odds ratios allow use of a single number to present results
  - probabilities differ according to values of Xs, and across continuous X variables

- They’re a good starting point
  - unfortunately, ORs are all you will see in many sociology papers

Logit & ologit questions

Could you explain the cutpoints in ologit, and how they affect probabilities?

- No need to give them much thought – rarely discussed, but can think of them like intercepts or thresholds that separate the different outcome levels
  - probability of falling into each category for reference group

❑ Technical note

For ordered logit, `predict, xb` produces $S_j = x_{1j}\beta_1 + x_{2j}\beta_2 + \cdots + x_{kj}\beta_k$. The ordered-logit predictions are then the probability that $S_j + u_j$ lies between a pair of cutpoints, κ_{i-1} and κ_i. Some handy formulas are

$$\Pr(S_j + u_j < \kappa) = 1/(1 + e^{S_j - \kappa})$$

$$\Pr(S_j + u_j > \kappa) = 1 - 1/(1 + e^{S_j - \kappa})$$

$$\Pr(\kappa_1 < S_j + u_j < \kappa_2) = 1/(1 + e^{S_j - \kappa_2}) - 1/(1 + e^{S_j - \kappa_1})$$

Logit & ologit questions: cutpoints cont.

```
ologit hap married if nmiss==0
```

hap	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
married	.955141	.0166754	57.28	0.000	.9224579	.9878241
/cut1	-1.500276	.0140264			-1.527768	-1.472785
/cut2	1.335536	.0135578			1.308963	1.362109

- P NotHappyMarried = 1/(1+exp(0.955--1.500)) = 0.079
- P NotHappySingle = exp(-1.500)/(1+exp(-1.500)) = 0.182

- P PrettyHappyMarried = 1/(1+exp(0.955-1.34))-0.079 = 0.516
- P PrettyHappySingle = exp(1.34)/(1+exp(1.34))-0.182 = 0.610

- P VerryHappyMarried = 1 – 0.079 – 0.516 = 0.405
- P VeryHappySingle = 1 – 0.182 – 0.61 = 0.208

Logit & ologit questions: cutpoints cont.

```
tab hap married if nmiss==0, column chi2 /*doesn't tell us direction*/
```

hap	married 0	married 1	Total
1	5,197 18.50	2,417 7.64	7,614 12.75
2	16,969 60.42	16,429 51.93	33,398 55.92
3	5,921 21.08	12,792 40.43	18,713 31.33
Total	28,087 100.00	31,638 100.00	59,725 100.00

Pearson chi2(2) = 3.3e+03 Pr = 0.000

= 0.079
= 0.182

= 0.516
= 0.610

= 0.405
= 0.208

```
ologit hap married if nmiss==0
/*compute predicted probabilites by married using cutpoints*/
generate probnothappymarried=1/(1+exp(_b[married]-_b[/cut1]))
generate probnothappysingle=exp(_b[/cut1])/(1+exp(_b[/cut1]))
generate probprettyhappymarried=1/(1+exp(_b[married]-_b[/cut2]))-probnothappymarried
generate probprettyhappysingle=exp(_b[/cut2])/(1+exp(_b[/cut2]))-probnothappysingle
generate probveryhappymarried=1-probnothappymarried-probprettyhappymarried
generate probveryhappysingle=1-probnothappysingle-probprettyhappysingle
sum probnothappymarried probprettyhappymarried probveryhappymarried ///
probnothappysingle probprettyhappysingle probveryhappysingle
```

Variable	Obs	Mean	Std. Dev.	Min	Max
probnothap~d	64,814	.0790433	0	.0790433	.0790433
probpretty~d	64,814	.5149251	0	.5149251	.5149251
probveryha~d	64,814	.4060316	0	.4060316	.4060316
probnothap~e	64,814	.1823843	0	.1823843	.1823843
probpretty~e	64,814	.6093706	0	.6093706	.6093706
probveryha~e	64,814	.2082451	0	.2082451	.2082451

```
mtable if married==1
```

1	2	3
0.079	0.515	0.406

```
mtable if married==0
```

1	2	3
0.182	0.609	0.208

Logit & ologit questions

Could we please review the proportional odds assumption (Brant test)?

- Assumes that the effects of any X are consistent across different thresholds
- Let's do an example by hand
  - requires some understanding of cumulative odds

```
tab hap if nmiss==0
```

hap	Freq.	Percent	Cum.
1	7,614	12.75	12.75
2	33,398	55.92	68.67
3	18,713	31.33	100.00
Total	59,725	100.00	

	NH	PH	VH
N	7614	33398	18713
Cumulative N at each level or above	59725	52111	18713
Cumulative proportion	1	0.87	0.31
Cumulative odds		6.84	0.46

- Cumulative proportion = cumulative N/ total
- Cumulative odds = CP/(1-CP)

Logit & ologit questions: prop. odds cont.

- Are odds for married proportional across thresholds of happiness?

```
tab hap married if nmiss==0, column
```

hap	married 0	married 1	Total
1	5,197 18.50	2,417 7.64	7,614 12.75
2	16,969 60.42	16,429 51.93	33,398 55.92
3	5,921 21.08	12,792 40.43	18,713 31.33
Total	28,087 100.00	31,638 100.00	59,725 100.00

Married	NH	PH	VH
N	2417	16429	12792
Cumulative N at each level or above	31638	29221	12792
Cumulative proportion	1	0.92	0.40
Cumulative odds		12.09	0.68
Cumulative logits		2.49	-0.39
Single	NH	PH	VH
N	5197	16969	5921
Cumulative N at each level or above	28087	22890	5921
Cumulative proportion	1	0.81	0.21
Cumulative odds		4.40	0.27
Cumulative logits		1.48	-1.32
Odds Ratio (Single/Married)		0.36	0.39
Odds Ratio (Married/Single)		2.74	2.54

```
ologit hap i.married if nmiss==0, or
```

hap	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.married	2.599037	.0433399	57.28	0.000	2.515465	2.685385
/cut1	-1.500276	.0140264			-1.527768	-1.472785
/cut2	1.335536	.0135578			1.308963	1.362109

```
brant
```

	chi2	p>chi2	df
All	7.41	0.006	1
1.married	7.41	0.006	1

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

Logit & ologit questions

What is the difference between how AME and MEM are calculated? I think I still get them a little mixed up and really understanding the difference here would aid my conceptual understanding of these marginal effects

- Each observation has a predicted probability given unique combination of Xs
- Marginal effect of any given X depends on value of all other Xs
- AME computes marginal effect for each observation and takes the average
- MEM computes marginal holding all other Xs at mean
- Often comparable when hold all Xs at global means
  - both are “averages” of the entire sample, just computed in different ways

Logit & ologit questions

- In Long/Freese on page 366, they talk about how marginal effect in GLM can change magnitude and sign with different values. What does this mean?

- Regression coef., w/o polynomial terms, cannot change sign across values of X

- However, marginal effects can flip direction w/o additional terms

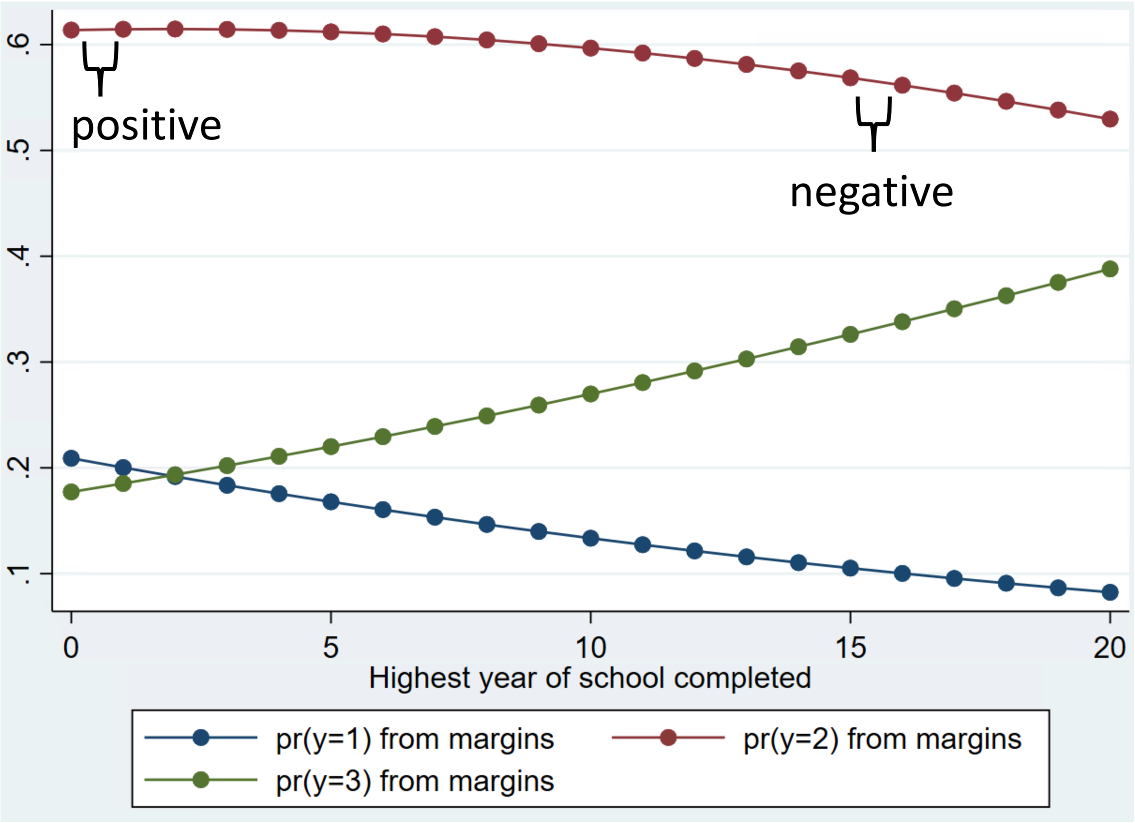
- Example of years of education on happiness in next slide

```
ologit hap c.age i.female i.nonwhite i.married c.educ if nmiss==0, or
```

hap	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	1.003459	.0004738	7.31	0.000	1.00253	1.004388
1.female	1.12516	.0183108	7.25	0.000	1.089837	1.161627
1.nonwhite	.7316936	.0154816	-14.76	0.000	.7019708	.7626749
1.married	2.509298	.0423914	54.46	0.000	2.427573	2.593774
educ	1.055456	.0027769	20.51	0.000	1.050027	1.060913
/cut1	-.6788447	.0467884			-.7705482	-.5871411
/cut2	2.187014	.0476849			2.093553	2.280474

- Coef. cannot flip signs
  - without polynomial

Logit & ologit questions: flip sign cont.




```
mchange educ, at(educ=0) atmeans stat(change) brief
```

	1	2	3
educ			
+1	-0.009	0.001	0.008
+SD	-0.027	0.001	0.026
Marginal	-0.009	0.001	0.008

```
mchange educ, at(educ=15) atmeans stat(change) brief
```

	1	2	3
educ			
+1	-0.005	-0.007	0.012
+SD	-0.015	-0.024	0.039
Marginal	-0.005	-0.007	0.012

- At zero-years of education an additional year of education increases the probability of being pretty happy, but at 15-years of education an additional year of education has a negative impact on the probability of being pretty happy

GLM interaction effects: moderation

- Log odds, and even odds ratios, provide limited interpretability
  - probability metric provides substantive interpretation
  - odds metric is linear, and probability metric is nonlinear
    - complicates interpretation of interaction effects

- Even if interaction term is significant in terms of log odds/ratios, it may NOT be significant in terms of probability, and vice versa
  - interaction terms (moderation) imply differences in differences, which in terms of probability can differ across values of other covariates
    - e.g., become in/significant, and/or even switch direction

- Takeaway: can NOT simply use coefficient (log odds/ratio) P-value to determine whether an interaction effect is present

GLM interaction effects: moderation (BLM)

- Let's consider whether race moderates the effects of education
  - begin with main effect only model

```
logit hap_dic c.age##c.age i.female c.educ i.nonwhite i.married ///
if nmiss==0, or /*educ=1.10252***, nonwhite=0.6566978***/
quietly fitstat, save /*let's save to compare with interaction model*/
```

hap_dic	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.9589154	.0038924	-10.34	0.000	.9513167	.9665748
c.age#c.age	1.000413	.0000405	10.22	0.000	1.000334	1.000493
1.female	1.093578	.0279077	3.51	0.000	1.040225	1.149667
educ	1.10252	.0044311	24.28	0.000	1.09387	1.111239
1.nonwhite	.6566978	.0190268	-14.51	0.000	.6204451	.6950688
1.married	2.787257	.0765109	37.34	0.000	2.641261	2.941323
_cons	3.436189	.3575823	11.86	0.000	2.802193	4.213628

- Both education and nonwhite are significant
- Let's see if AME of edu differs by race

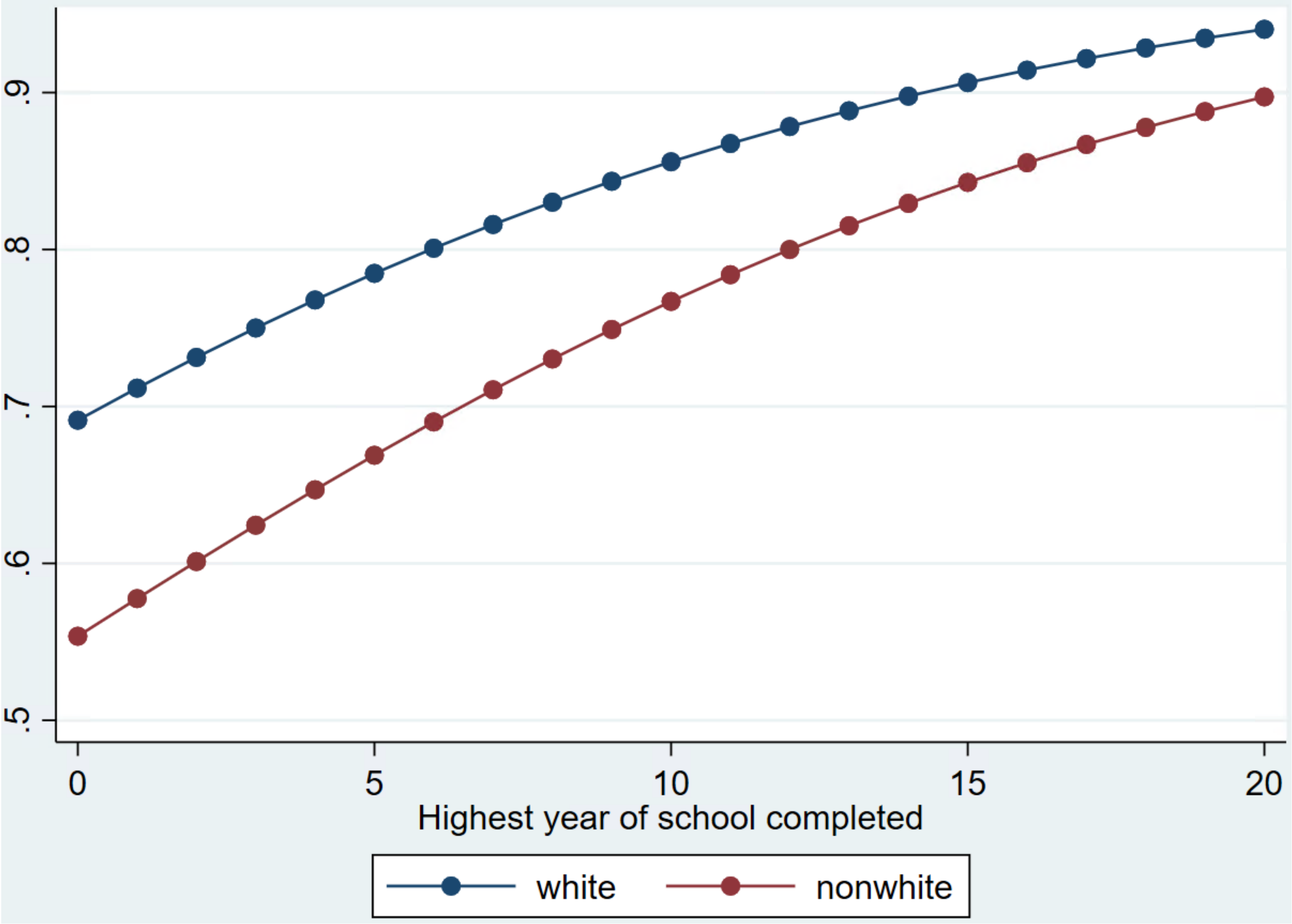
```
mtable, dydx(educ) at(nonwhite=(0 1)) post
/*let's check if they are statistically differnt*/
mlincom 2-1
```

	lincom	pvalue	ll	ul
1	0.003	0.000	0.003	0.004

- The AME of edu differs by race, but this does NOT mean that race moderates the effects of education on happiness
- Before testing for moderation, let's check out race-specific predicted probability by education

Race-specific edu pattern: main effect model

```
mgen if nonwhite==0, at(educ=(0(1)20)) replace stub(nonint0) predlab(white) atmeans
mgen if nonwhite==1, at(educ=(0(1)20)) replace stub(nonint1) predlab(nonwhite) atmea
twoway connected nonint0prl nonint1prl nonint0educ
```



Let’s test for moderation: edu * nonwhite

```
logit hap_dic c.age##c.age i.female c.educ##i.nonwhite i.married ///
if nmiss==0, or /*educ=1.118406***, nonwhite=1.12477, educ*race=0.9556351***/
fitstat, dif /*better fit compared to model without interaction*/
```

hap_dic	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.9582151	.0038911	-10.51	0.000	.9506189	.965872
c.age#c.age	1.00042	.0000405	10.39	0.000	1.000341	1.0005
1.female	1.097049	.0279999	3.63	0.000	1.04352	1.153323
educ	1.118406	.0053674	23.32	0.000	1.107936	1.128976
1.nonwhite	1.12477	.1157476	1.14	0.253	.9193236	1.376129
nonwhite#c.educ						
1	.9556351	.0079252	-5.47	0.000	.9402275	.9712952
1.married	2.790466	.0766269	37.37	0.000	2.64425	2.944767
_cons	2.925217	.3160289	9.94	0.000	2.366997	3.615086

Note: Likelihood-ratio test assumes saved model nested in current model.

Difference of 18.988 in BIC provides **very strong** support for **current** model.

- Educ significant but nonwhite not significant, also interaction significant
- Need to compare AME of edu averaging over only nonwhites and whites

```
mtable, dydx(educ) over(nonwhite) post
/*let's check if they are statistically diffrent*/
mlincom 2-1
```

	lincom	pvalue	ll	ul
1	-0.001	0.595	-0.003	0.002

- The effects of edu do not differ by race, but we also need to consider whether the effects of race differ by education

GLM interaction effects: moderation

```
mtable, dydx(nonwhite) over(educ) stat(ci) post
mlincom 2-1
mlincom 4-3
mlincom 6-5
mlincom 8-7
mlincom 10-9
mlincom 12-11
mlincom 14-13
mlincom 16-15
mlincom 18-17
mlincom 20-19
mlincom 21-20
```

	d Pr(y)	ll	ul
0	0.025	-0.018	0.068
1	0.015	-0.023	0.053
2	0.005	-0.028	0.039
3	-0.004	-0.034	0.026
4	-0.012	-0.038	0.014
5	-0.019	-0.041	0.003
6	-0.026	-0.045	-0.007
7	-0.031	-0.047	-0.016
8	-0.037	-0.050	-0.024
9	-0.042	-0.053	-0.031
10	-0.046	-0.055	-0.037
11	-0.050	-0.059	-0.042
12	-0.051	-0.058	-0.043
13	-0.055	-0.063	-0.048
14	-0.057	-0.065	-0.049
15	-0.059	-0.068	-0.051
16	-0.057	-0.066	-0.048
17	-0.057	-0.067	-0.047
18	-0.058	-0.069	-0.047
19	-0.057	-0.069	-0.045
20	-0.057	-0.069	-0.044

mlincom 2-1

	lincom	pvalue	ll	ul
1	-0.010	0.000	-0.015	-0.006

mlincom 4-3

	lincom	pvalue	ll	ul
1	-0.009	0.000	-0.013	-0.005

mlincom 6-5

	lincom	pvalue	ll	ul
1	-0.007	0.000	-0.011	-0.003

mlincom 8-7

	lincom	pvalue	ll	ul
1	-0.005	0.003	-0.009	-0.002

mlincom 10-9

	lincom	pvalue	ll	ul
1	-0.005	0.000	-0.008	-0.003

mlincom 12-11

	lincom	pvalue	ll	ul
1	-0.005	0.000	-0.007	-0.002

mlincom 14-13

	lincom	pvalue	ll	ul
1	-0.005	0.000	-0.007	-0.002

mlincom 16-15

mlincom 16-15

	lincom	pvalue	ll	ul
1	-0.002	0.013	-0.004	-0.000

mlincom 18-17

	lincom	pvalue	ll	ul
1	-0.000	0.531	-0.002	0.001

mlincom 20-19

	lincom	pvalue	ll	ul
1	0.001	0.089	-0.000	0.002

mlincom 21-20

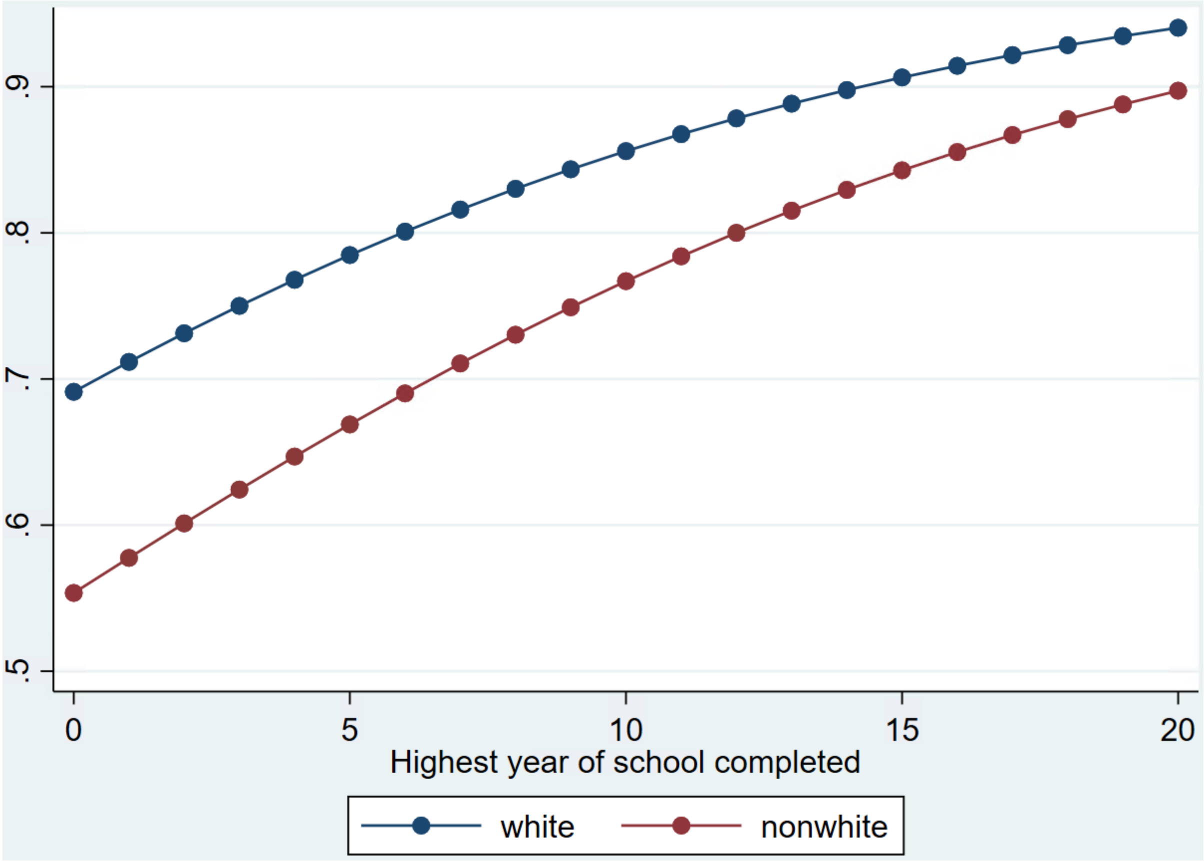
	lincom	pvalue	ll	ul
1	0.000	0.775	-0.001	0.001

- Race AME differs by edu
  - edu moderates race
- Should probably collapse
  - sensitive to cell size
    - tab nonwhite educ

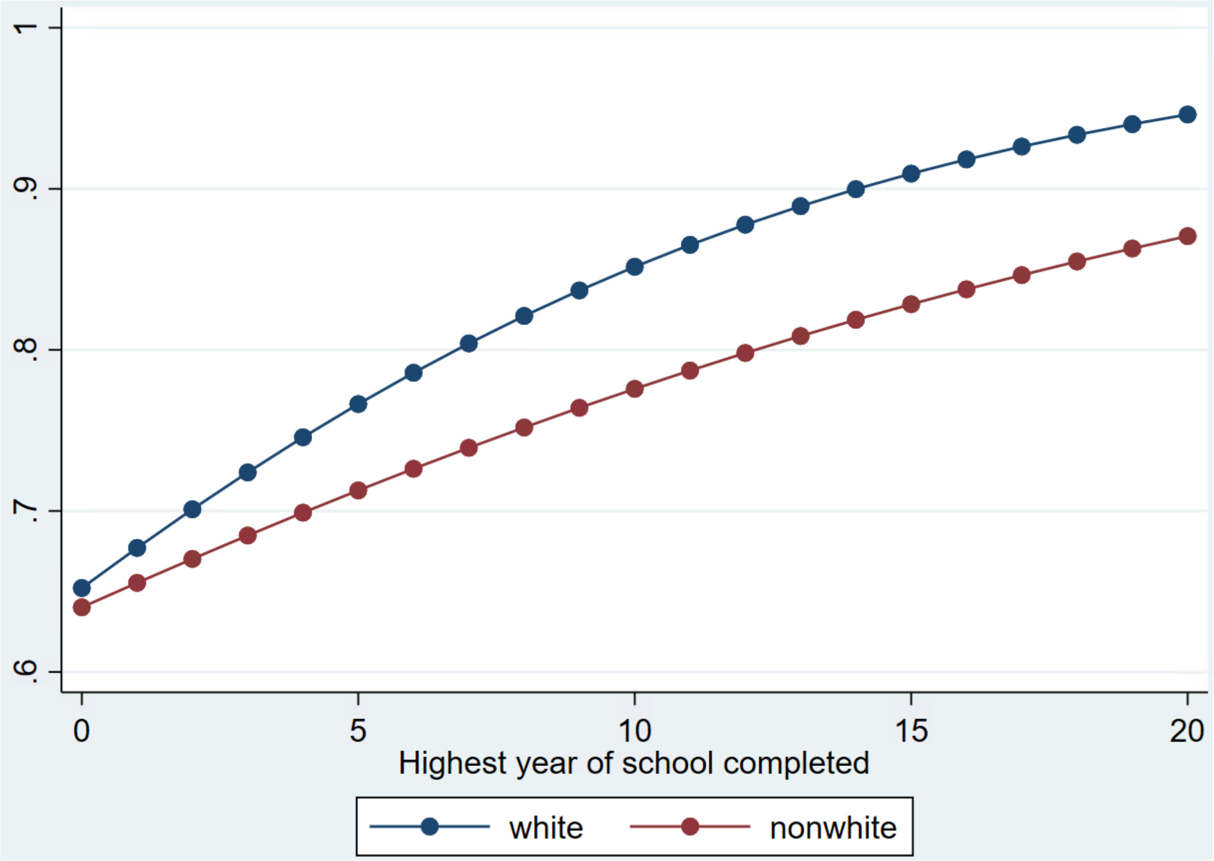
```
tab educ nonwhite if nmiss==0
```

Compare main effect vs. interaction model

Main effect only model



Interaction model



- Caution regarding “real” interpretation, but results from interaction model reflect diminishing returns hypothesis

Code from Long & Mustillo (2021)

- Use to download stata programs used for paper

```
search groupsbrm
help groupsbrm
```

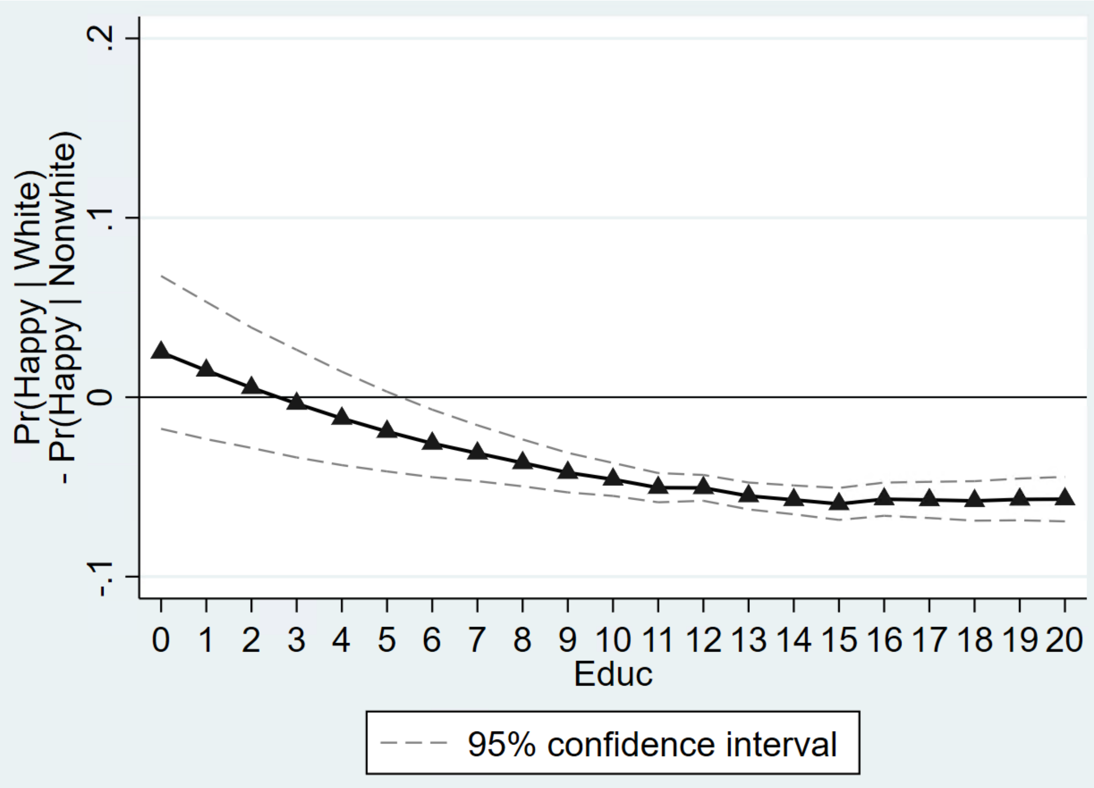
- Programs use macros
  - user-defined shortcuts

```
//  Options for graphs
* prob curves
global LINwht clcol(blue) lpat(solid) lwid(*1.2) ///
              msym(S) mcol(blue) msiz(*.93)
global LINnon clcol(black) lpat(solid) lwid(*1.2) ///
              msym(O) mcol(black)  msiz(*1.1)
```

- Examples in .do with just a few minor replacements

- You can do the same

```
twoway  ///
   (connected Adcd_prl      Adceduc, $LINdc) /// line
   (connected Adcll1 Adcul1 Adceduc, $LINci), /// ci
   ytitle("Pr(Happy | White)" "- Pr(Happy | Nonwhite)") ///
   xtitle(Educ) xlabel(0(1)20) ylabel(-.1(.1).2, grid gmin gmax) ///
   yline(0, lcol(black) lwid(*.6)) ///
   legend(pos(6) ring(1) cols(1) order(3) symxsize(7)) scale(1.2)
```



Nominal outcomes

- DV has more than two categories

- differences between categories are qualitative
  - order does NOT matter
    - republican, democrat, independent

- no natural ordering
  - (1) = white, (2) = black, (3) = Asian, same as
  - (1) = white, (2) = Asian, (3) = black, same as
  - (1) = black, (2) = white, (3) = Asian, same as
  - (1) = black, (2) = Asian, (3) = white, same as
  - (1) = Asian, (2) = black, (3) = white, same as…
  - you get the idea

Multinomial Logistic Regression

- Categorical DV
  - ASSUMES unordered responses

- Compares multiple groups simultaneously
  - G_1 vs $G_{2,}$ G_1 vs G_3, G_2 vs G_3

- Simultaneous binary logistic regression models, but
  - better than BLR b/c doesn't drop information on model-by-model basis

- Alternative if ologit violates proportional odds assumption
  - downside is complex interpretation

Mlogit

- Computes probability of falling in $\geq$3 categories

- Cannot use set of binary logit models b/c samples would differ
  - drops those not included in any of the 2 among 3+ categories

- Mlogit simultaneously computes probability for $\geq$3 categories
  - base reference doesn't matter for predictions
    - but, estimated parameters will differ

$$\Pr(y = m \mid x) = \frac{\exp(x\beta_{m|b})}{\sum_{j=1}^{J} \exp(x\beta_{j|b})}$$

Political party affiliation: original

```
tab partyid, m
```

Political party affiliation	Freq.	Percent	Cum.
STRONG DEMOCRAT	10,378	16.01	16.01
NOT STR DEMOCRAT	13,294	20.51	36.52
IND,NEAR DEM	7,792	12.02	48.55
independent	9,888	15.26	63.80
IND,NEAR REP	5,721	8.83	72.63
NOT STR REPUBLICAN	9,933	15.33	87.95
STRONG REPUBLICAN	6,318	9.75	97.70
OTHER PARTY	1,072	1.65	99.36
DK	11	0.02	99.37
NA	407	0.63	100.00
Total	64,814	100.00	

- Let’s collapse SD/D, and SR/R
  - for simplicity
- consider “other party” missing
  - for simplicity
- Recode into 3 parties
  - (1) democrat, (2) republican, (3) independent
    - order doesn’t matter

Political party affiliation: recode

```
gen polparty=.
replace polparty=1 if partyid==0 | partyid==1 /*democrat*/
replace polparty=2 if partyid==5 | partyid==6 /*republican*/
replace polparty=3 if partyid==2 | partyid==3 | partyid==4 /*idependent*/
tab polparty partyid, m
/*let's add labels - mlogit can get confusing*/
label variable polparty "Political Affiliation"
label define polparty 1 Democrat 2 Republican 3 Independent
label values polparty "polparty"
```

```
tab polparty if nmiss==0
```

Political Affiliation	Freq.	Percent	Cum.
Democrat	21,980	37.64	37.64
Republican	14,940	25.58	63.22
Independent	21,477	36.78	100.00
Total	58,397	100.00	

- Label values are strongly encouraged when using mlogit

Multiple BRM example: don't really do this

- First, create variables for possible bivariate contrast
- Dem-Ind, Rep-Ind, Dem-Rep

dem_ind	Freq.	Percent	Cum.
0	21,477	36.78	36.78
1	21,980	37.64	74.42
.	14,940	25.58	100.00
Total	58,397	100.00	

Political Affiliation	Freq.	Percent	Cum.
Democrat	21,980	37.64	37.64
Republican	14,940	25.58	63.22
Independent	21,477	36.78	100.00
Total	58,397	100.00	

rep_ind	Freq.	Percent	Cum.
0	21,477	36.78	36.78
1	14,940	25.58	62.36
.	21,980	37.64	100.00
Total	58,397	100.00	

dem_rep	Freq.	Percent	Cum.
0	14,940	25.58	25.58
1	21,980	37.64	63.22
.	21,477	36.78	100.00
Total	58,397	100.00	

Does education predict political affiliation?

Logistic regression — Number of obs = 43,457; LR chi2(1) = 123.79; Prob > chi2 = 0.0000; Pseudo R2 = 0.0021

Log likelihood = -30057.292

dem_ind	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
educ	-.0332116	.0029937	-11.09	0.000	-.0390793	-.027344
_cons	.4439192	.0391384	11.34	0.000	.3672094	.520629

Logistic regression — Number of obs = 36,417; LR chi2(1) = 191.76; Prob > chi2 = 0.0000; Pseudo R2 = 0.0039

Log likelihood = -24556.562

rep_ind	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
educ	.0490625	.0035666	13.76	0.000	.0420721	.056053
_cons	-1.003937	.0479544	-20.94	0.000	-1.097926	-.9099485

Logistic regression — Number of obs = 36,920; LR chi2(1) = 538.06; Prob > chi2 = 0.0000; Pseudo R2 = 0.0108

Log likelihood = -24646.634

dem_rep	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
educ	-.077546	.0033976	-22.82	0.000	-.0842052	-.0708868
_cons	1.386202	.0453745	30.55	0.000	1.29727	1.475135

Multinomial logistic regression — Number of obs = 58,397; LR chi2(2) = 557.74; Prob > chi2 = 0.0000; Pseudo R2 = 0.0044

Log likelihood = -63048.078

polparty	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Democrat						
educ	-.0339939	.0030266	-11.23	0.000	-.0399259	-.0280619
_cons	.4538368	.0395437	11.48	0.000	.3763325	.5313411
Republican						
educ	.0459947	.0034404	13.37	0.000	.0392517	.0527378
_cons	-.9638454	.0463415	-20.80	0.000	-1.054673	-.8730178
Independent	(base outcome)					

- D versus R = difference between two sets of coef.
  - (0.046) – (-0.034) = 0.08
- Rerun mlogit with base (1)
- Close but not exact

Mlogit: base outcomes

```
mlogit polparty educ if nmiss==0, base(3)
```

polparty	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Democrat						
educ	-.0339939	.0030266	-11.23	0.000	-.0399259	-.0280619
_cons	.4538368	.0395437	11.48	0.000	.3763325	.5313411
Republican						
educ	.0459947	.0034404	13.37	0.000	.0392517	.0527378
_cons	-.9638454	.0463415	-20.80	0.000	-1.054673	-.8730178
Independent	(base outcome)					

```
mlogit polparty educ if nmiss==0, base(2)
```

polparty	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Democrat						
educ	-.0799886	.0034276	-23.34	0.000	-.0867066	-.0732707
_cons	1.417682	.0457542	30.98	0.000	1.328006	1.507359
Republican	(base outcome)					
Independent						
educ	-.0459947	.0034404	-13.37	0.000	-.0527378	-.0392517
_cons	.9638454	.0463415	20.80	0.000	.8730178	1.054673

```
mlogit polparty educ if nmiss==0, base(1)
```

polparty	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Democrat	(base outcome)					
Republican						
educ	.0799886	.0034276	23.34	0.000	.0732707	.0867066
_cons	-1.417682	.0457542	-30.98	0.000	-1.507359	-1.328006
Independent						
educ	.0339939	.0030266	11.23	0.000	.0280619	.0399259
_cons	-.4538368	.0395437	-11.48	0.000	-.5313411	-.3763325

- Must know base to interpret coef.
  - therefore labels strongly suggested
- Default base is largest category
- Can use listcoef to see all contrasts

```
listcoef
```

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	-0.0800	-23.337	0.000	0.923	0.776
Democrat vs Independent	-0.0340	-11.232	0.000	0.967	0.898
Republican vs Democrat	0.0800	23.337	0.000	1.083	1.289
Republican vs Independent	0.0460	13.369	0.000	1.047	1.157
Independent vs Democrat	0.0340	11.232	0.000	1.035	1.114
Independent vs Republican	-0.0460	-13.369	0.000	0.955	0.864

Mlogit: multivariate model

- Results can become overwhelming when there are more covariates
  - and/or when there are more outcome categories

```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married c.educ ///
if nmiss==0, base(1)
```

polparty	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Democrat	(base outcome)					
Republican						
hap	.1874158	.0181361	10.33	0.000	.1518697	.2229619
age	-.034744	.0036832	-9.43	0.000	-.0419629	-.0275251
c.age#c.age	.0003445	.0000359	9.59	0.000	.0002741	.0004149
1.female	-.2070969	.0223374	-9.27	0.000	-.2508774	-.1633164
1.nonwhite	-1.829464	.0383019	-47.76	0.000	-1.904534	-1.754393
1.married	.2338762	.0239378	9.77	0.000	.186959	.2807933
educ	.0640285	.0036251	17.66	0.000	.0569235	.0711336
_cons	-.595581	.1022443	-5.83	0.000	-.7959762	-.3951859
Independent						
hap	-.0600455	.0159191	-3.77	0.000	-.0912464	-.0288445
age	-.0284918	.0033145	-8.60	0.000	-.0349881	-.0219955
c.age#c.age	.0001043	.0000333	3.13	0.002	.000039	.0001696
1.female	-.2838982	.0198731	-14.29	0.000	-.3228487	-.2449477
1.nonwhite	-.8140462	.024187	-33.66	0.000	-.8614518	-.7666406
1.married	-.0599199	.0211156	-2.84	0.005	-.1013058	-.018534
educ	.0078315	.0032286	2.43	0.015	.0015036	.0141594
_cons	1.434134	.0892763	16.06	0.000	1.259155	1.609112

Variable: hap (sd=0.637)

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	-0.1874	-10.334	0.000	0.829	0.888
Republican vs Democrat	0.1874	10.334	0.000	1.206	1.127
Republican vs Independent	0.2475	13.757	0.000	1.281	1.171
Independent vs Republican	-0.2475	-13.757	0.000	0.781	0.854

Variable: age (sd=17.586)

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	0.0347	9.433	0.000	1.035	1.842
Republican vs Democrat	-0.0347	-9.433	0.000	0.966	0.543
Republican vs Independent	-0.0063	-1.706	0.088	0.994	0.896
Independent vs Republican	0.0063	1.706	0.088	1.006	1.116

Variable: c.age#c.age (sd=1776.600)

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	-0.0003	-9.590	0.000	1.000	0.542
Republican vs Democrat	0.0003	9.590	0.000	1.000	1.844
Republican vs Independent	0.0002	6.578	0.000	1.000	1.532
Independent vs Republican	-0.0002	-6.578	0.000	1.000	0.653

Variable: 1.female (sd=0.496)

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	0.2071	9.271	0.000	1.230	1.108
Republican vs Democrat	-0.2071	-9.271	0.000	0.813	0.902
Republican vs Independent	0.0768	3.510	0.000	1.080	1.039
Independent vs Republican	-0.0768	-3.510	0.000	0.926	0.963

Variable: 1.nonwhite (sd=0.395)

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	1.8295	47.764	0.000	6.231	2.059
Republican vs Democrat	-1.8295	-47.764	0.000	0.160	0.486
Republican vs Independent	-1.0154	-25.532	0.000	0.362	0.670
Independent vs Republican	1.0154	25.532	0.000	2.761	1.493

Variable: 1.married (sd=0.499)

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	-0.2339	-9.770	0.000	0.791	0.890
Republican vs Democrat	0.2339	9.770	0.000	1.263	1.124
Republican vs Independent	0.2938	12.455	0.000	1.342	1.158
Independent vs Republican	-0.2938	-12.455	0.000	0.745	0.864

Variable: educ (sd=3.172)

	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	-0.0640	-17.663	0.000	0.938	0.816
Republican vs Democrat	0.0640	17.663	0.000	1.066	1.225
Republican vs Independent	0.0562	15.439	0.000	1.058	1.195
Independent vs Republican	-0.0562	-15.439	0.000	0.945	0.837

Independence of Alternatives assumption

- Adding or deleting alternative does not affect the odds among the remaining alternatives
  - (1) car, (2) red bus, (3) blue bus
    - (see Long & Freese, pp 407)

- Hausman-McFadden test of IAA
- Small-Hsiao test of IAA
  - sometimes provide conflicting results

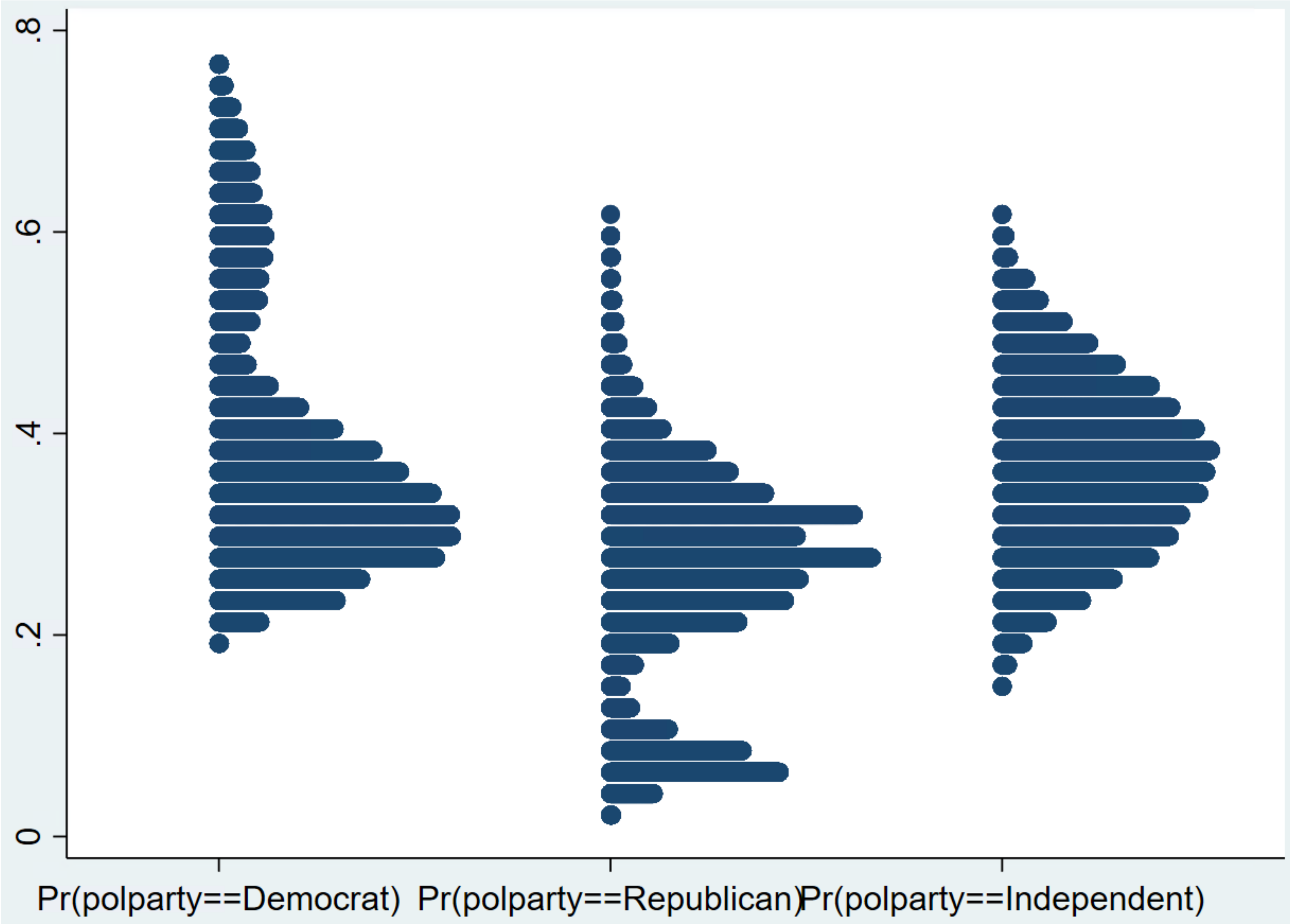
- Tests are not great
- so, rely on theory
  - alternatives plausibly assumed to be distinct and weighted independently

IAA test examples

- I can’t get either to run
  - mlogtest, hausman
  - mlogtest, smhsiao
- Not encouraged anyways
- See here for more

What about magnitude? Predicted probability

- Plot the predicted probabilities to examine the distribution



Marginal effects

- Marginal effect: Δ in the predicted probability given a Δ in X
  - holding all other Xs constant
    - Is there a meaningful way to hold all other Xs constant?
- Average marginal effect (AME): the average of the marginal effect for all observations
  - Likely, no one is "average." What about underrepresented groups?
- Marginal effect at the mean (MEM): all other Xs held at their means
  - Many mean values are often meaningless (e.g., dummy Xs)
- Marginal effect at representative values (MER): all other Xs held at substantively meaningful values
  - What are "meaningful" values? Can become quickly overwhelmed with details

Average marginal effect (AME)

- Avg. Δ in probability for Δ in X, holding all else constant

	Democrat	Republi~n	Indepen~t
hap			
+1	-0.010	0.041	-0.031
p-value	0.002	0.000	0.000
+SD	-0.006	0.026	-0.020
p-value	0.003	0.000	0.000
Marginal	-0.008	0.039	-0.031
p-value	0.009	0.000	0.000
age			
+1	0.003	0.001	-0.004
p-value	0.000	0.000	0.000
+SD	0.029	0.041	-0.070
p-value	0.000	0.000	0.000
Marginal	0.003	0.001	-0.004
p-value	0.000	0.000	0.000
female			
1 vs 0	0.056	-0.011	-0.045
p-value	0.000	0.003	0.000
nonwhite			
1 vs 0	0.271	-0.204	-0.067
p-value	0.000	0.000	0.000
married			
1 vs 0	-0.012	0.047	-0.035
p-value	0.004	0.000	0.000
educ			
+1	-0.007	0.011	-0.004
p-value	0.000	0.000	0.000
+SD	-0.021	0.035	-0.014
p-value	0.000	0.000	0.000
Marginal	-0.007	0.011	-0.004
p-value	0.000	0.000	0.000

- On average, a one-unit increase in happiness is associated with a 0.04 increase in the probability of being a Republican, a 0.01 decrease in being a Democrat, and a 0.03 decrease in being an Independent
- AMEs sum to 0

Marginal effect at the mean (MEM)

	Democrat	Republi~n	Indepen~t
hap			
+1	-0.009	0.040	-0.031
p-value	0.008	0.000	0.000
+SD	-0.005	0.025	-0.019
p-value	0.013	0.000	0.000
Marginal	-0.007	0.037	-0.030
p-value	0.031	0.000	0.000
age			
+1	0.003	0.001	-0.004
p-value	0.000	0.000	0.000
+SD	0.038	0.034	-0.072
p-value	0.000	0.000	0.000
Marginal	0.003	0.001	-0.004
p-value	0.000	0.000	0.000
female			
1 vs 0	0.061	-0.011	-0.049
p-value	0.000	0.001	0.000
nonwhite			
1 vs 0	0.272	-0.194	-0.079
p-value	0.000	0.000	0.000
married			
1 vs 0	-0.011	0.045	-0.034
p-value	0.013	0.000	0.000
educ			
+1	-0.007	0.011	-0.004
p-value	0.000	0.000	0.000
+SD	-0.022	0.035	-0.012
p-value	0.000	0.000	0.000
Marginal	-0.007	0.010	-0.004
p-value	0.000	0.000	0.000

- For respondents average on all characteristics, a one-unit increase in happiness is associated with a 0.04 increase in the probability of being a Republican, a 0.01 decrease in being a Democrat, and a 0.03 decrease in being an Independent

Marginal effect at representative values (MER)

```
mchange female, at(female=1 hap=3 married=1 age=40 nonwhite=0 educ=12)
```

	Democrat	Republi~n	Indepen~t
female			
1 vs 0	0.053	-0.011	-0.042
p-value	0.000	0.008	0.000

	hap	age	female	nonwhite	married	educ
at	3	40	1	0	1	12

```
mchange female, at(female=1 hap=3 married=1 age=40 nonwhite=1 educ=12)
```

	Democrat	Republi~n	Indepen~t
female			
1 vs 0	0.064	-0.010	-0.055
p-value	0.000	0.000	0.000

	hap	age	female	nonwhite	married	educ
at	3	40	1	1	1	12

- Among those who are white very happy, married, age 40, white, HS educated, the probability of being a Democrat is 0.053 greater, Republican is 0.011 lower, Independent is 0.042 lower for females vs. males

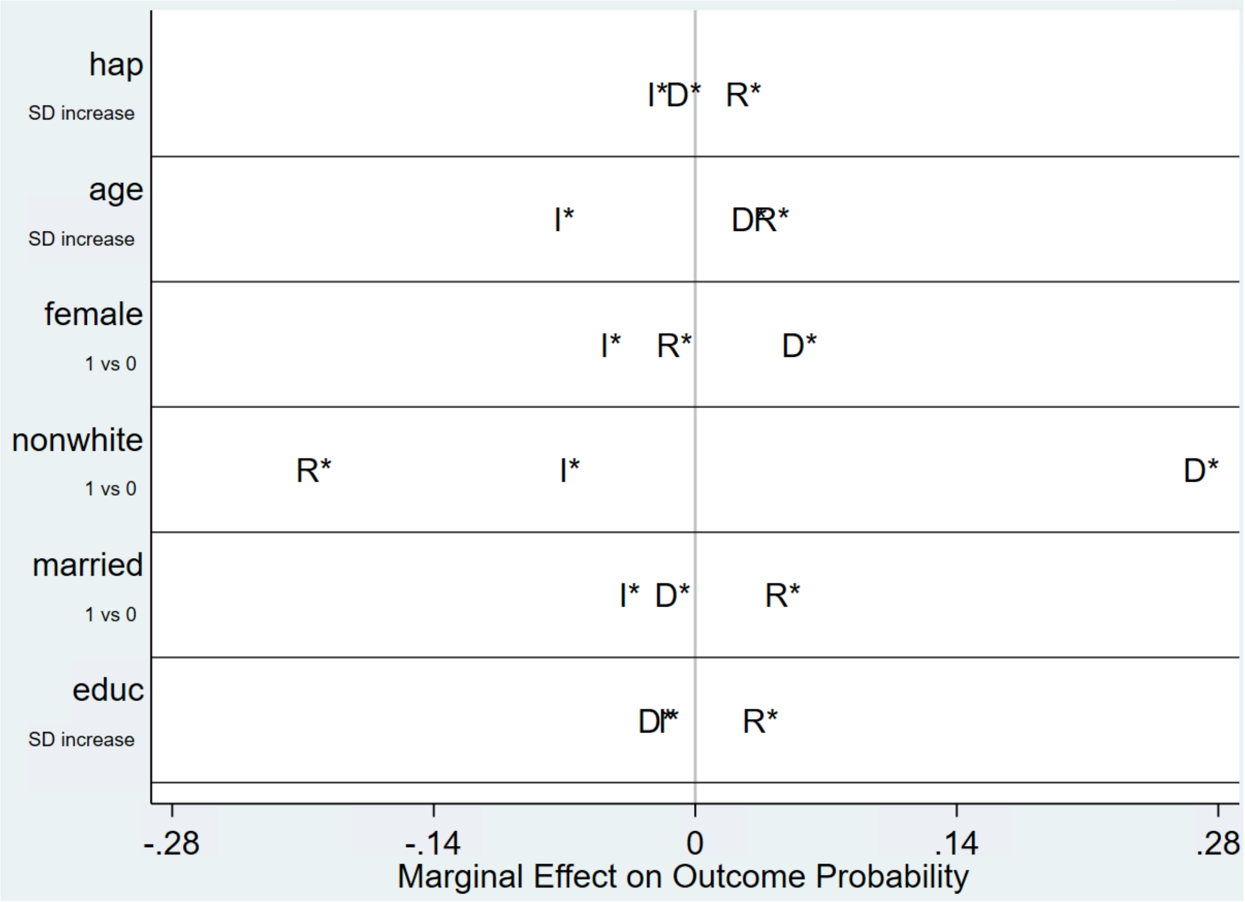
- Among those who are Nonwhite, very happy, married, age 40, HS educated, the probability of being a Democrat is 0.064 greater, Republican is 0.010 lower, Independent is 0.055 lower for females vs. males

Plotting marginal effects

- The amount of information tabled by mchange can be overwhelming
  - plots can sometimes effectively show this same information

	Democrat	Republi~n	Indepen~t
hap			
+1	-0.010	0.041	-0.031
p-value	0.002	0.000	0.000
+SD	-0.006	0.026	-0.020
p-value	0.003	0.000	0.000
Marginal	-0.008	0.039	-0.031
p-value	0.009	0.000	0.000
age			
+1	0.003	0.001	-0.004
p-value	0.000	0.000	0.000
+SD	0.029	0.041	-0.070
p-value	0.000	0.000	0.000
Marginal	0.003	0.001	-0.004
p-value	0.000	0.000	0.000
female			
1 vs 0	0.056	-0.011	-0.045
p-value	0.000	0.003	0.000
nonwhite			
1 vs 0	0.271	-0.204	-0.067
p-value	0.000	0.000	0.000
married			
1 vs 0	-0.012	0.047	-0.035
p-value	0.004	0.000	0.000
educ			
+1	-0.007	0.011	-0.004
p-value	0.000	0.000	0.000
+SD	-0.021	0.035	-0.014
p-value	0.000	0.000	0.000
Marginal	-0.007	0.011	-0.004
p-value	0.000	0.000	0.000

```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married c.educ ///
if nmiss==0, base(1)
mchange
mchangeplot, min(-.28) max(.28) sig(.05)
```



Predicted probabilities: across categorical X

- Predicted probability of political affiliation by education
  - all else at global means

```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married i.educat ///
if nmiss==0, base(1)
mtable, at(educat=(0 1 2)) atmeans
```

	educat	Democrat	Republican	Independent
1	0	0.446	0.161	0.393
2	1	0.392	0.214	0.394
3	2	0.373	0.261	0.366

- The probability of being a Democrat decreases from 0.45 to 0.37 when comparing those with <HS to those with >HS education, holding all else at their global means

- For those who are average on all other characteristics, <HS educated folks are much more likely to be Democrats and far less likely to be Republicans

- The difference between educational group probabilities should be comparable to the MEM

Predicted probabilities: across categorical X

- If interested in educational difference by race we may want to consider local means for the other controls rather than global means

- The more you add the more complex to interpret

```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married i.educat ///
if nmiss==0, base(1)
mtable, over(educat nonwhite) atmeans
```

	hap	age	female	nonwhite	married	educat	Democrat	Republ~n	Indepe~t
1	2.13	53.4	.552	0	.545	0	0.413	0.212	0.375
2	2	48.6	.587	1	.359	0	0.658	0.050	0.292
3	2.21	46.2	.591	0	.599	1	0.340	0.268	0.393
4	2.02	39.8	.589	1	.367	1	0.583	0.069	0.348
5	2.27	44.4	.524	0	.557	2	0.311	0.320	0.369
6	2.1	40.2	.601	1	.393	2	0.579	0.089	0.332

Ideal types

- Set values of X to create hypothetical observation
  - age 40, 12-years education

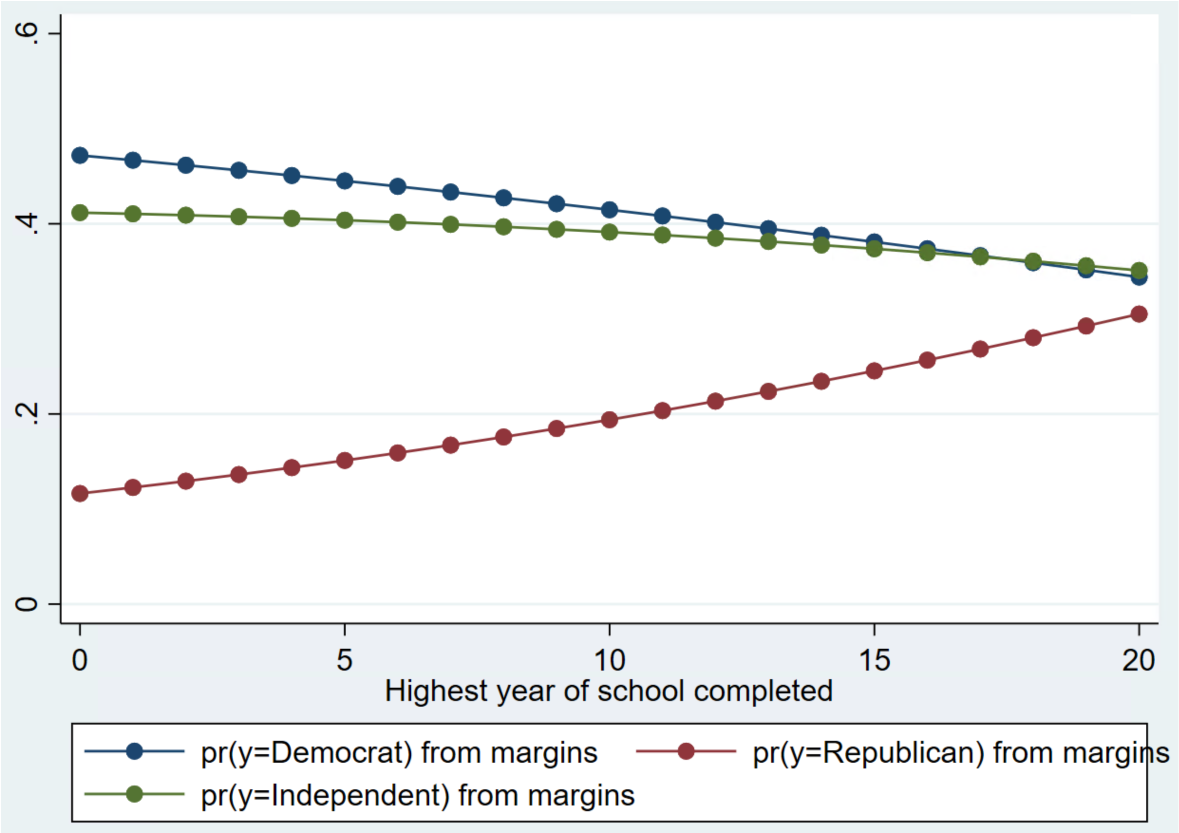
```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married c.educ ///
if nmiss==0, base(1)
mtable, at(age==40 female==0 educ==12 married==0 nonwhite==0) ///
at (age==40 female==0 educ==12 married==0 nonwhite==1) ///
at (age==40 female==1 educ==12 married==0 nonwhite==0) ///
at (age==40 female==1 educ==12 married==0 nonwhite==1) ///
at (age==40 female==0 educ==12 married==1 nonwhite==0) ///
at (age==40 female==0 educ==12 married==1 nonwhite==1) ///
at (age==40 female==1 educ==12 married==1 nonwhite==0) ///
at (age==40 female==1 educ==12 married==1 nonwhite==1)
```

	female	nonwhite	married	Democrat	Republican	Independent
1	0	0	0	0.302	0.235	0.462
2	0	1	0	0.555	0.069	0.376
3	1	0	0	0.359	0.227	0.414
4	1	1	0	0.620	0.063	0.316
5	0	0	1	0.292	0.287	0.421
6	0	1	1	0.557	0.088	0.355
7	1	0	1	0.347	0.277	0.376
8	1	1	1	0.622	0.080	0.299

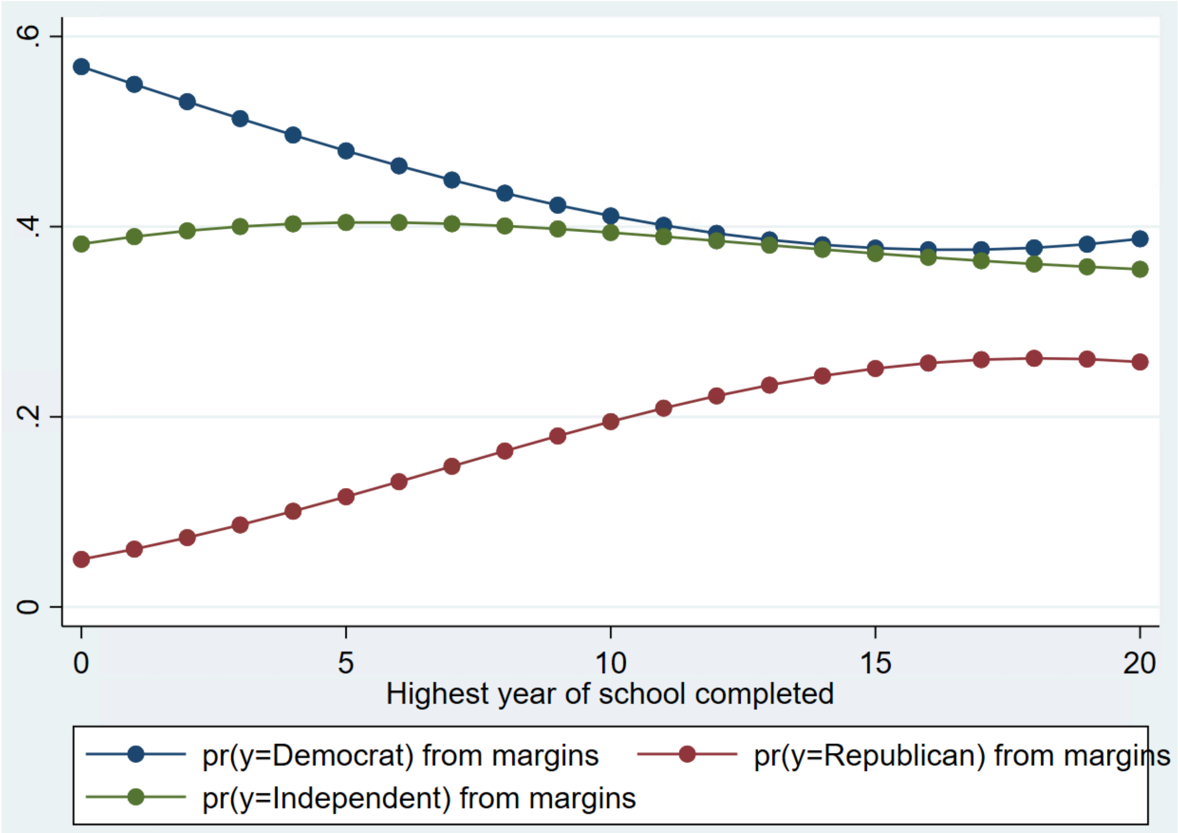
- Interpretation?
- Get complex, fast
- Maybe turn on/off IV between “meaningful groups” to help “tell a story”
  - guided by theory

Graphing predicted probabilities: cont. IV

```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married c.educ ///
if nmiss==0, base(1)
mgen, at(educ=(0(1)20)) atmeans stub(mnl_) replace
graph twoway connected mnl_pr1 mnl_pr2 mnl_pr3 mnl_educ, ///
```

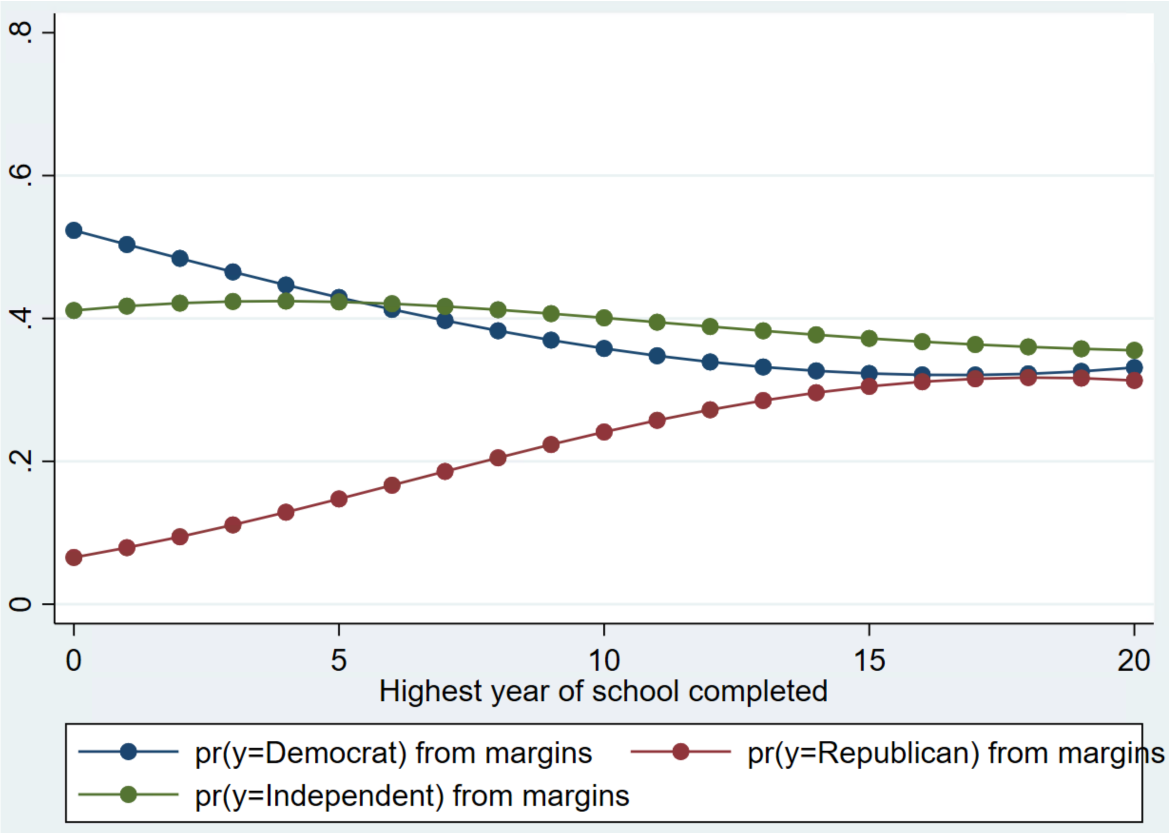



```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married c.educ##c.educ //
if nmiss==0, base(1)
mgen, at(educ=(0(1)20)) atmeans stub(mnl_) replace
graph twoway connected mnl_pr1 mnl_pr2 mnl_pr3 mnl_educ
```

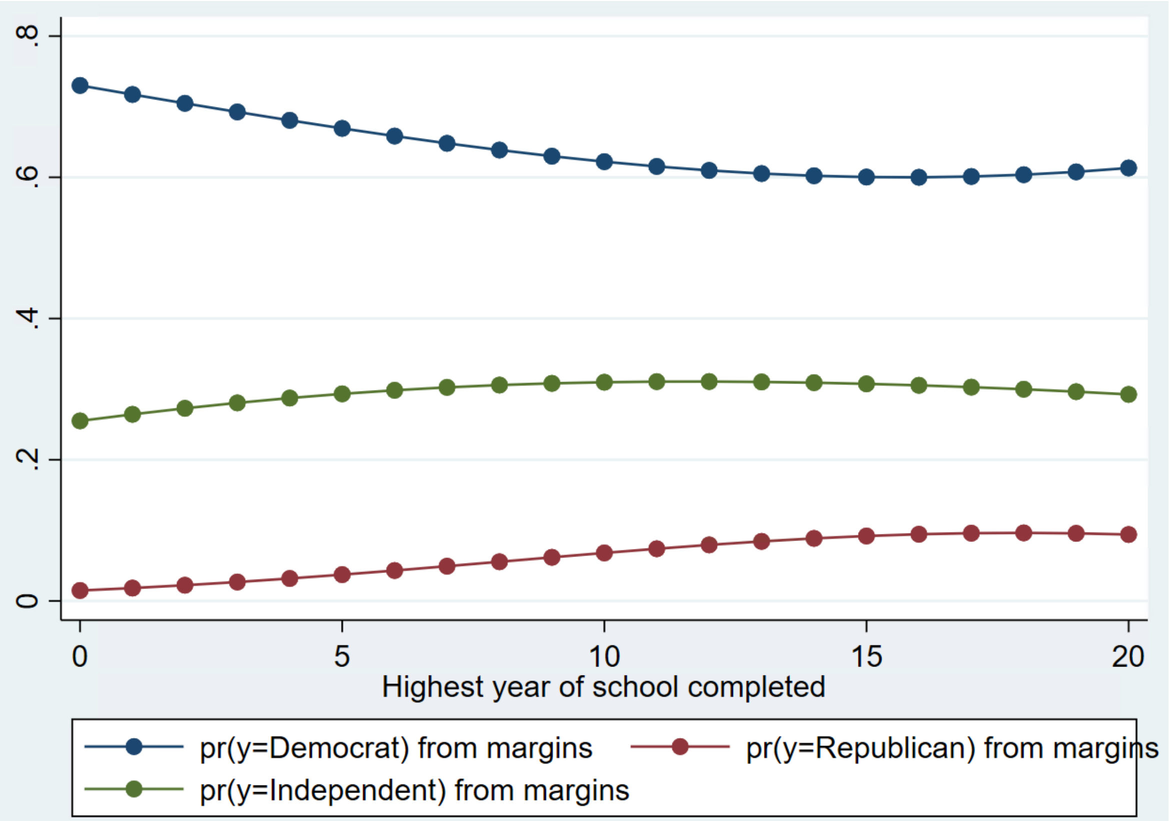


Graphing predicted probabilities: cont. IV

```
mgen, at(educ=(0(1)20)nonwhite=0) atmeans stub(mnl_) replace
graph twoway connected mnl_pr1 mnl_pr2 mnl_pr3 mnl_educ, ylab(0(.2).8)
```




```
mgen, at(educ=(0(1)20)nonwhite=1) atmeans stub(mnl_) replace
graph twoway connected mnl_pr1 mnl_pr2 mnl_pr3 mnl_educ, ylab(0(.2).8)
```



Relative Risk Ratios

- A little more informative than with logit and ologit
  - shows dynamics among the outcomes

```
mlogit polparty hap c.age##c.age i.female i.nonwhite i.married i.educat ///
if nmiss==0, base(1) rrr
```

polparty	RRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Democrat	(base outcome)					
Republican						
hap	1.199854	.0217999	10.03	0.000	1.157879	1.243351
age	.9660205	.00356	-9.38	0.000	.9590683	.9730232
c.age#c.age	1.000351	.0000359	9.77	0.000	1.000281	1.000421
1.female	.8081348	.0180985	-9.51	0.000	.7734296	.8443972
1.nonwhite	.160234	.0061395	-47.79	0.000	.1486416	.1727305
1.married	1.27093	.0304997	9.99	0.000	1.212536	1.332136
educat						
1	1.514266	.0487768	12.88	0.000	1.421621	1.612949
2	1.937608	.0584304	21.93	0.000	1.826405	2.055581
_cons	.7981574	.0768348	-2.34	0.019	.6609179	.9638948
Independent						
hap	.940539	.0149707	-3.85	0.000	.9116499	.9703436
age	.9717758	.0032174	-8.65	0.000	.9654903	.9781023
c.age#c.age	1.000109	.0000333	3.26	0.001	1.000043	1.000174
1.female	.7506084	.0149344	-14.42	0.000	.7219008	.7804575
1.nonwhite	.4449654	.0107494	-33.52	0.000	.424388	.4665405
1.married	.9403264	.0198781	-2.91	0.004	.9021621	.9801052
educat						
1	1.14246	.0308111	4.94	0.000	1.083639	1.204473
2	1.113841	.028405	4.23	0.000	1.059536	1.170928
_cons	4.241093	.3535261	17.33	0.000	3.601835	4.993806

- Females have 19% lower odds than males to be Republican compared to Democrat, all else held constant

- A one unit increase in happiness is associated with a 1.20 increase in the odds of being Republican compared to Democrat

Relative Risk Ratios

- Need to examine for comparisons among all pairs of outcomes
  - let's first consider just a single variable

```
listcoef nonwhite, help
```

		b	z	P>|z|	e^b	e^bStdX
Democrat	vs Republican	1.8311	47.790	0.000	6.241	2.060
Democrat	vs Independent	0.8098	33.520	0.000	2.247	1.377
Republican	vs Democrat	-1.8311	-47.790	0.000	0.160	0.485
Republican	vs Independent	-1.0214	-25.677	0.000	0.360	0.668
Independent	vs Democrat	-0.8098	-33.520	0.000	0.445	0.726
Independent	vs Republican	1.0214	25.677	0.000	2.777	1.497

```
       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
```

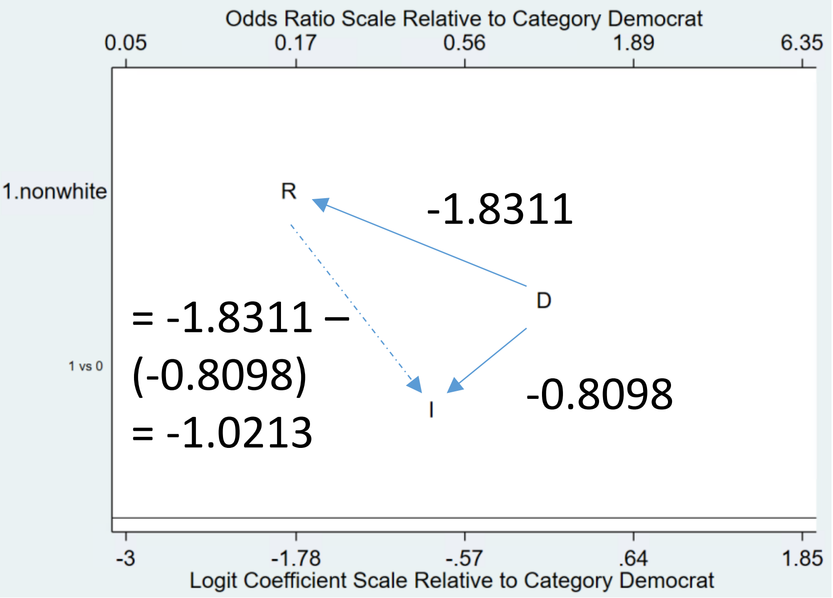
- The odds of being Democrat or Independent versus Republican are substantially greater among nonwhites compared to whites, 524% and 125% respectively, all else held constant

- Being nonwhite reduces the odds of being a Republican versus an Independent by 64%, and an Independent versus a Democrat by 55%, holding all other variables constant.

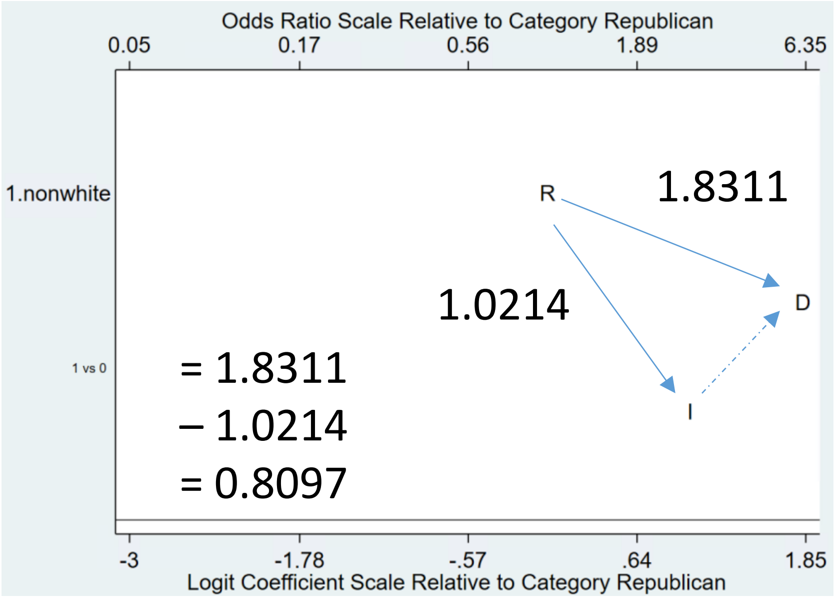
Relative Risk Ratios

- A lot of information, even for a single variable
  - can be helpful to plot

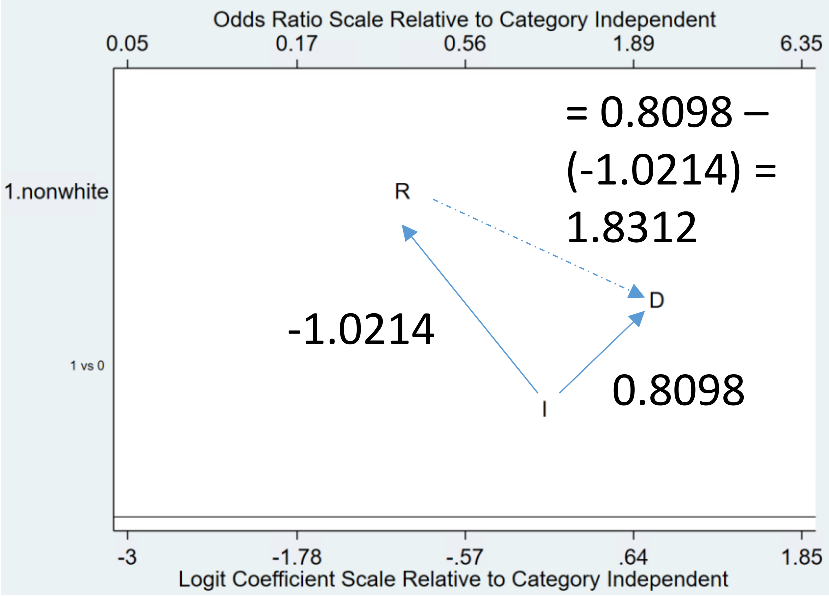
`mlogitplot nonwhite, base(1) ormin(.05) ormax(6.35)`



`mlogitplot nonwhite, base(2) ormin(.05) ormax(6.35)`



`mlogitplot nonwhite, base(3) ormin(.05) ormax(6.35)`



	b	z	P>|z|	e^b	e^bStdX
Democrat vs Republican	1.8311	47.790	0.000	6.241	2.060
Democrat vs Independent	0.8098	33.520	0.000	2.247	1.377
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Comparing Ologit and Mlogit

Recall ologit on happiness violated

- the parallel regression assumption

- Whether coef. equal when each combo of cats. modeled separately
  - like a series of binary regressions

```
ologit hap c.age##c.age i.female i.nonwhite c.educ i.married, or
brant
```

	chi2	p>chi2	df
All	388.86	0.000	6
age	11.27	0.001	1
c.age#c.age	3.52	0.061	1
1.female	2.60	0.107	1
1.nonwhite	43.14	0.000	1
educ	177.35	0.000	1
1.married	3.69	0.055	1

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

- One solution is to use a multinomial logistic model

Ologit vs. mlogit

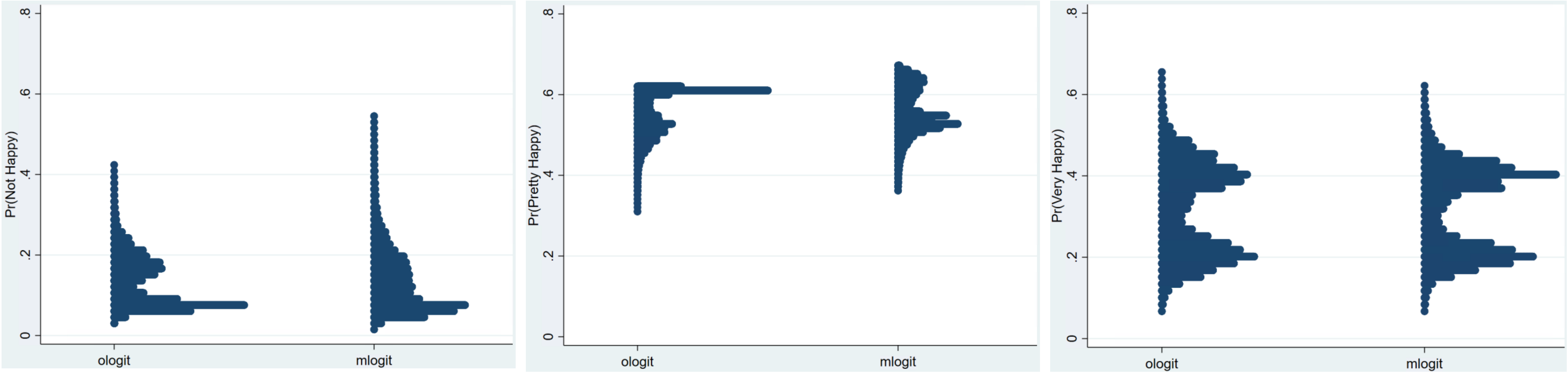
hap	RRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1	(base outcome)					
2						
age	.9653763	.004031	-8.44	0.000	.9575079	.9733093
c.age#c.age	1.000325	.0000417	7.80	0.000	1.000243	1.000407
1.female	1.052803	.0275776	1.96	0.049	1.000116	1.108265
1.nonwhite	.6804816	.0203107	-12.90	0.000	.6418154	.7214772
educ	1.094133	.0045206	21.77	0.000	1.085309	1.10303
1.married	2.102778	.0594115	26.31	0.000	1.989499	2.222507
_cons	2.603152	.278064	8.96	0.000	2.111425	3.209396
3						
age	.9457446	.0043656	-12.08	0.000	.9372268	.9543398
c.age#c.age	1.000597	.0000458	13.04	0.000	1.000507	1.000687
1.female	1.194004	.0341742	6.20	0.000	1.128868	1.262899
1.nonwhite	.6009205	.0205699	-14.88	0.000	.5619269	.64262
educ	1.12017	.0050788	25.03	0.000	1.11026	1.130168
1.married	4.86895	.1500923	51.35	0.000	4.583485	5.172194
_cons	.8282195	.0978802	-1.59	0.111	.6569755	1.044099

- Compared to males, females have 19% and 5% greater odds of being very or pretty happy vs. not happy, respectively
- ologit results: compare

hap	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.9669484	.0026115	-12.44	0.000	.9618434	.9720805
c.age#c.age	1.000375	.0000269	13.94	0.000	1.000322	1.000428
1.female	1.123892	.0183011	7.17	0.000	1.088589	1.16034
1.nonwhite	.7445495	.0157875	-13.91	0.000	.7142407	.7761445
educ	1.06084	.0028206	22.21	0.000	1.055326	1.066382
1.married	2.67136	.0467923	56.10	0.000	2.581205	2.764663
/cut1	-1.379002	.068731			-1.513712	-1.244291
/cut2	1.494651	.068699			1.360003	1.629299

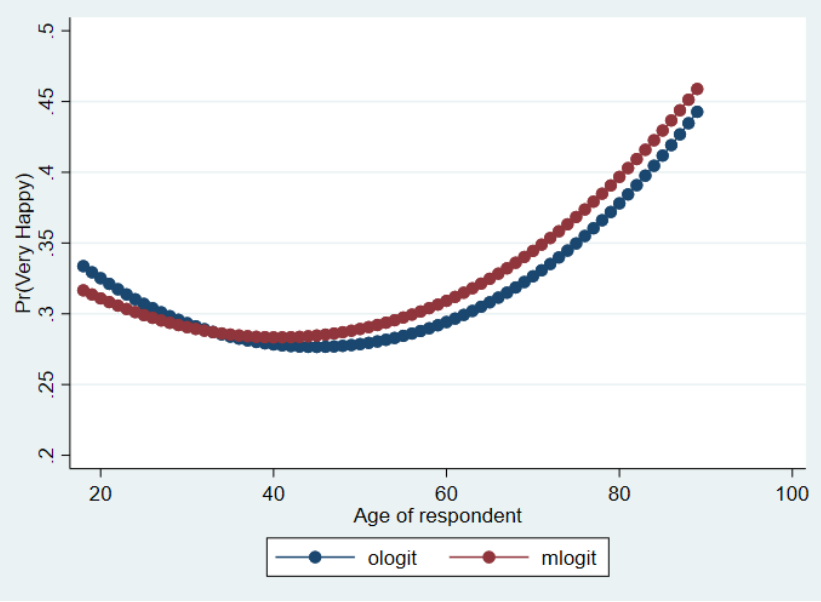
- “listcoef” for all comparisons

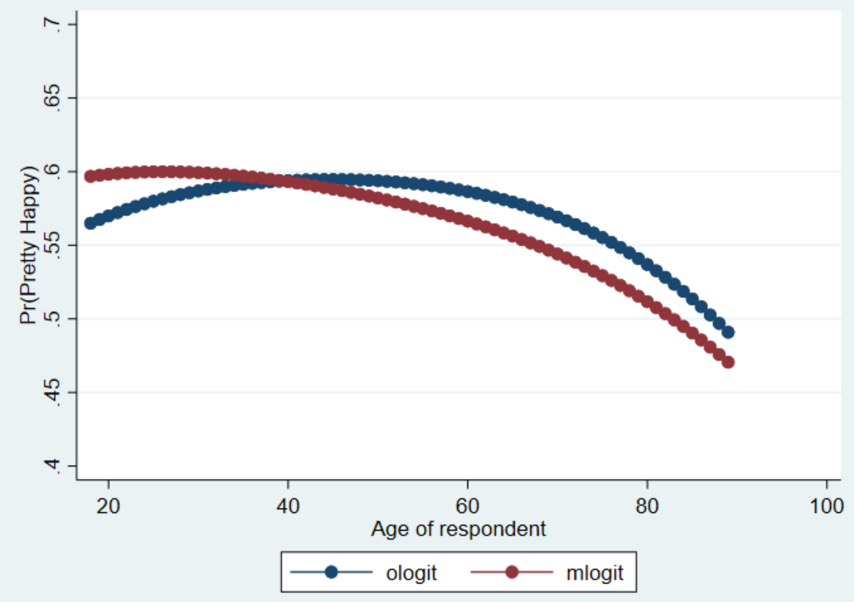
Ologit vs. mlogit: compare predicted probs.

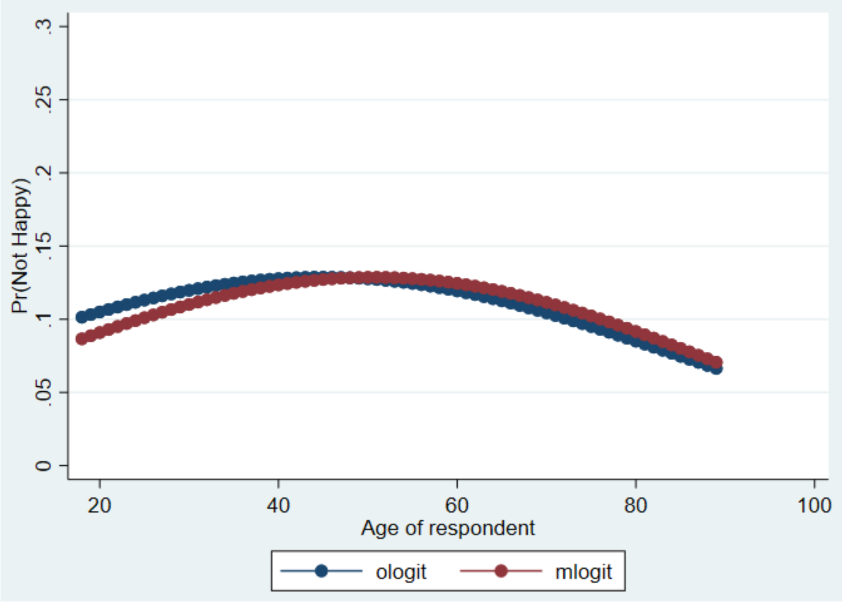


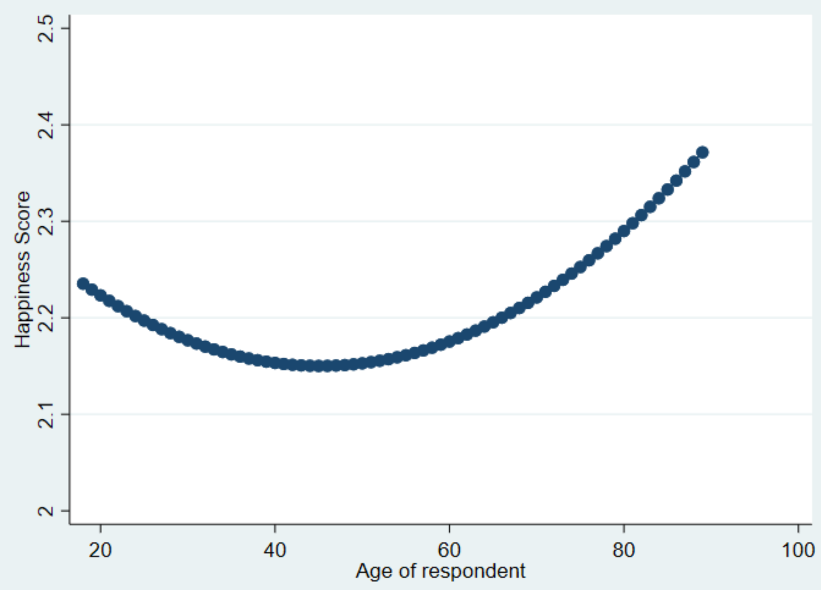
- Somewhat different…enough to yield substantively different findings?

Ologit vs. mlogit vs. ols









- Sometimes model selection leads to major differences in substantive findings

- Not the case here