Quantitative Data Analysis II

SOC 781

Ordered outcomes

Ordinal logit and probit models

Today we will…

- cover regression for ordered outcomes
- graphing output
- compare ologit and oprobit models
    - model diagnostics

Ordered outcomes

- DV has more than two categories

- differences between categories are quantitative
  - order matters
    - <HS, HS, GTHS

- distance is unknown
  - 0=strongly disagree, 1=disagree, 2=agree, 3=strongly agree
    - Is the difference between 0 & 1 the same as between 2 & 3?

Odds ratios

hap	married 0	1	Total
1	5,197	2,417	7,614
2	16,969	16,429	33,398
3	5,921	12,792	18,713
Total	28,087	31,638	59,725

- Recall, ORs = odds of one group divided by the odds of another group
- First, let's compute each group's respective odds

- Pr(m, not too happy) = 2,417/31,638 = 0.08
- Pr(nm, not too happy) = 5,197/28,087 = 0.19
- Pr(m, pretty happy) = 16,429/31,638 = 0.52
- Pr(nm, pretty happy) = 16,969/28,087 = 0.60
- Pr(m, very happy) =12,792/31,638 = 0.40 sum=1
- Pr(nm, very happy) =5,921/28,087 = 0.21 sum=1

Odds ratios

hap	married 0	1	Total
1	5,197	2,417	7,614
2	16,969	16,429	33,398
3	5,921	12,792	18,713
Total	28,087	31,638	59,725

- Recall, ORs = odds of one group divided by the odds of another group
- Yes, but what's the comparison?
  - when binary it was 0
- Now need to compute 2 odds ratios and take a weighted average
  - the number of computations depends on the number of categories (n – 1)
- First, very happy(VH) vs pretty happy(PH), not too happy(NTH) &
- then VH, PH vs NTH

- Pr(m, VH vs. PH, NTH) = 12,792 /(16,429 + 2,417) = 0.68
- Pr(nm, VH vs. PH, NTH) = 5,921/(16,969 + 5,197) = 0.27
- OR m vs nm = 0.68/0.27 = 2.54

Odds ratios

hap	married 0	1	Total
1	5,197	2,417	7,614
2	16,969	16,429	33,398
3	5,921	12,792	18,713
Total	28,087	31,638	59,725

- Now the odds for VH, PH vs NTH

- Pr(m, VH, PH vs. NTH) = (12,792+16,429) /(2,417) = 12.09
- Pr(nm, VH, PH vs. NTH) = (5,921+16,969)/(5,197) = 4.40
- OR m vs nm = 12.09/4.40 = 2.75

- Next take weighted average of 2.54 & 2.75
  - How to weight? Luckily Stata does this for us
    - should be in ballpark of (2.54+2.75)/2 = 2.65

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

hap	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
married	2.599037	.0433399	57.28	0.000	2.515465	2.685385

- Before interpret let's consider the ologit model

Ordered Logistic Regression

- Categorical DV that's rank ordered
  - ASSUMES equal distance between each outcome category
    - parallel regression (proportional odds) assumption
- OLS often used if $\geq$5 categories
  - still violates linearity and constant error variance
  - sometimes trade off for interpretation sake
    - if substantively comparable to ologit findings

Ologit

- MLE function similar to logit
  - except constrains β_0=0, and gets rid of one of the “unknowns” in the model
- Slope same for each category → parallel regression assumption
  - each unit increase in x associated w/ β increase in log odds of higher category
- However, pred. prob. Δ based on cutpoints (τ “tau”)

$$\log\left(\frac{p(y > 1)}{p(y \leq 1)}\right) = \tau_1 + b_1 x_1 + b_2 x_2$$

$$\log\left(\frac{p(y > 2)}{p(y \leq 2)}\right) = \tau_2 + b_1 x_1 + b_2 x_2$$

Ologit example: odds ratios

- Without “or” command will get log odds

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

hap	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.0336101	.0027008	-12.44	0.000	-.0389036	-.0283166
c.age#c.age	.0003749	.0000269	13.94	0.000	.0003221	.0004276
1.female	.1167978	.0162837	7.17	0.000	.0848823	.1487132
1.nonwhite	-.2949759	.0212041	-13.91	0.000	-.3365352	-.2534166
educ	.0590606	.0026588	22.21	0.000	.0538495	.0642718
1.married	.9825876	.0175163	56.10	0.000	.9482563	1.016919

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

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

- ORs are simply exponentiated log odds
  - exp(-0.0336101) = 0.9669484

- Just like with the binary logit,
  - but interpretation is a little more complex

Interpretation: OR > 1 (dummies)

- Similar interpretation as logit
  - except, outcome's reference category

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

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
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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

- The odds of being very happy vs. pretty happy or not too happy are 1.12 greater for females than males, all else equal

- Or, 12% greater
  - 1.12 – 1 = 0.12

Interpretation: OR < 1 (dummies)

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

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
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1.married	2.67136	.0467923	56.10	0.000	2.581205	2.764663

- The odds of being very happy vs. pretty happy or not too happy are 0.74 lower for nonwhites than whites, all else equal
  - the same could be said for very happy or pretty happy vs. not too happy

- Or, 26% lower
  - 1 - 0.74 = .26

Reverse option w/ listcoef

- Automatically computes based on upward comparisons
  - lower vs. higher outcomes

- Previous example: VH(3) vs. PH(2), NTH(1) & VH(3), PH(2) vs NTH(1)

- Can request to compute downward comparisons
  - higher vs. lower outcomes

- Use “reverse” option
  - NTH(1) vs. PH(2), VH(3) & NTH(1), PH(2), vs VH(3)

- Sometimes easier to only report increases in odds
  - rather than decreases

Interpretation: reverse option

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

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
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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

- The odds of reporting greater happiness are 0.74 lower for nonwhites than whites, all else equal

```
listcoef, reverse help
```

	b	z	P>|z|	e^b	e^bStdX	SDofX
age	-0.0336	-12.445	0.000	1.034	1.805	17.575
c.age#c.age	0.0004	13.935	0.000	1.000	0.514	1774.940
1.female	0.1168	7.173	0.000	0.890	0.944	0.497
1.nonwhite	-0.2950	-13.911	0.000	1.343	1.123	0.395
educ	0.0591	22.213	0.000	0.943	0.829	3.179
1.married	0.9826	56.096	0.000	0.374	0.612	0.499

- The odds of reporting lower happiness are 1.34 times greater for nonwhites than whites, all else equal

- Positive ORs may be more intuitive, but
- switching from higher to lower outcome may be more confusing
  - do what works for you

Interpretation: OR (continuous)

- Similar interpretation as logit
  - except, outcome's reference category

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

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
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- The odds of being very happy vs. pretty happy or not too happy increase by 1.06 with each additional year of education, all else equal

- Or, increase by 6% with each additional year of education
  - 1.06 – 1 = 0.06

Parallel regression assumption: Brant test

- 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
```

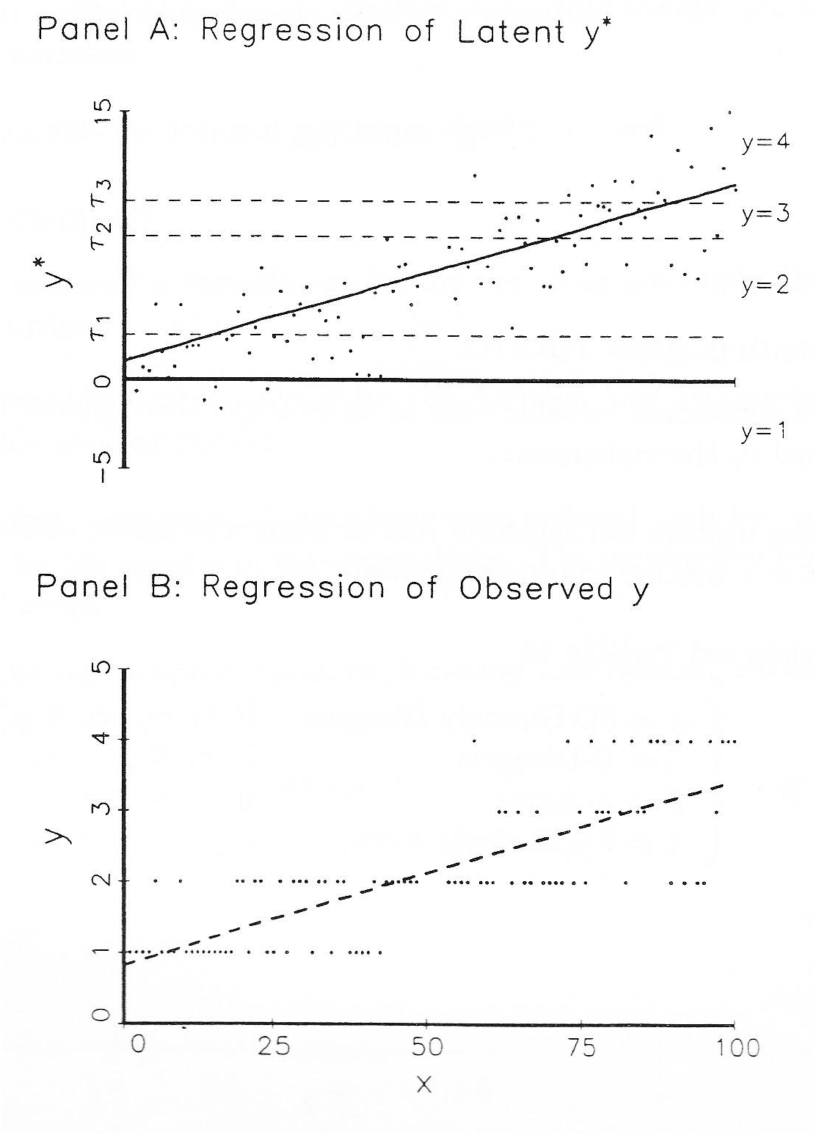
	chi2	p>chi2	df
All	388.86	0.000	6
age	11.27	0.001	1
c.age#c.age	3.52	0.061	1
1.female	2.60	0.107	1
1.nonwhite	43.14	0.000	1
educ	177.35	0.000	1
1.married	3.69	0.055	1

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

- Often violated, rarely (IMO) reported in publications
  - we can use a mlogit to address this issue (Week 10)
    - let’s move on with example as if not violated (gologit advanced)

Cutpoints: latent-variable example

- Y is observed, but Y* is not
  - treat Y as a continuous unmeasured latent variable Y*
- Y* has cutpoints
  - value on Y depends on whether crossed threshold
- Shouldn't use OLS b/c Y* is unobserved



Ologit: cutpoints

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
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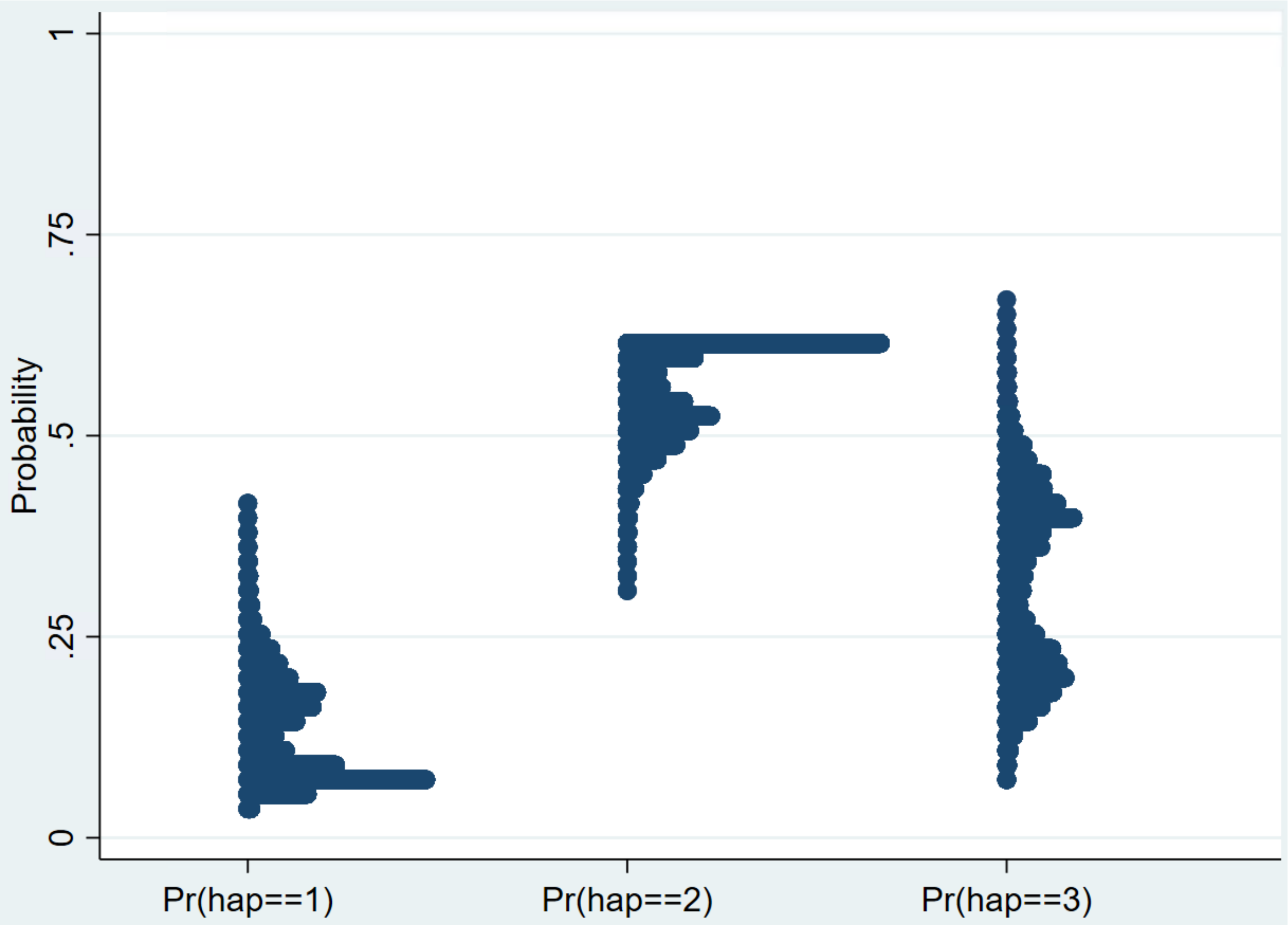
educ	1.06084	.0028206	22.21	0.000	1.055326	1.066382
1.married	2.67136	.0467923	56.10	0.000	2.581205	2.764663
/cut1	-1.379002	.068731			-1.513712	-1.244291
/cut2	1.494651	.068699			1.360003	1.629299

- Stata assumes the intercept is 0
- Cutpoints = #categories – 1
- Don’t need to consider for OR interpretation
- Used in calculations for other postestimation statistics
  - e.g., predicted probabilities; Stata does this for us

What about magnitude? Predicted probability

- Plot the predicted probabilities to examine the distribution



Marginal effects: similar to BRM

- 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): continuous

- Avg. Δ in probability for Δ in education (years), holding all else constant

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

	1	2	3
educ			
+1	-0.006	-0.006	0.012
p-value	0.000	0.000	0.000
+SD	-0.019	-0.020	0.039
p-value	0.000	0.000	0.000
Marginal	-0.006	-0.006	0.012
p-value	0.000	0.000	0.000

Average predictions

	1	2	3
Pr(y|base)	0.128	0.560	0.312

- On average, each additional year of edu. is associated with a 0.012 increase in the probability of being very happy, a 0.006 decrease in the probability of being pretty happy, and a 0.006 decrease in the probability of being not too happy
- AMEs sum to 0

- Average predicted probability of reporting not too happy is 0.128, pretty happy is 0.560, and very happy is 0.312

```
/*let's compute the average probability*/
egen mprvery=mean(prvery) if nmiss==0
egen mprpretty=mean(prpretty) if nmiss==0
egen mprnot=mean(prnot) if nmiss==0
/*should be close to sample mean*/
tab hap if nmiss==0
sum mprnot mprpretty mprvery /*0.13, 0.56, 0.31*/
```

Variable	Obs	Mean
mprnot	59,725	.1279951
mprpretty	59,725	.5596014
mprvery	59,725	.3124034

Average marginal effect (AME): categorical

- Avg. Δ in probability for Δ in education (groups), holding all else constant

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

	1	2	3
educat			
1 vs 0	-0.025	-0.015	0.040
p-value	0.000	0.000	0.000
2 vs 0	-0.051	-0.040	0.091
p-value	0.000	0.000	0.000
2 vs 1	-0.026	-0.026	0.051
p-value	0.000	0.000	0.000

- On average, the probability of being very happy is 0.040 greater for those with a HS education, and 0.091 greater for those with >HS education, versus those with <HS education

- On average, the probability of being not too happy is 0.025 lower for those with a HS education, and 0.051 lower for those with >HS education, versus those with <HS education

- We can go on and on…
  - consider how you can best “tell the story”

Marginal effect at the mean (MEM)

- Summary table for all Xs

```
mchange, atmeans statistics(ci) decimals(4)
```

	1	2	3
age			
+1	-0.0001	-0.0001	0.0003
LL	-0.0002	-0.0002	0.0001
UL	-0.0000	-0.0000	0.0005
+SD	-0.0136	-0.0127	0.0263
LL	-0.0157	-0.0147	0.0224
UL	-0.0116	-0.0107	0.0303
Marginal	-0.0001	-0.0001	0.0002
LL	-0.0002	-0.0002	-0.0000
UL	0.0000	0.0000	0.0004
female			
1 vs 0	-0.0129	-0.0101	0.0230
LL	-0.0165	-0.0129	0.0166
UL	-0.0093	-0.0073	0.0294
nonwhite			
1 vs 0	0.0369	0.0221	-0.0591
LL	0.0316	0.0195	-0.0667
UL	0.0423	0.0248	-0.0514
educat			
1 vs 0	-0.0264	-0.0121	0.0385
LL	-0.0322	-0.0147	0.0303
UL	-0.0206	-0.0094	0.0467
2 vs 0	-0.0530	-0.0364	0.0894
LL	-0.0584	-0.0397	0.0815
UL	-0.0476	-0.0331	0.0973
2 vs 1	-0.0266	-0.0243	0.0509
LL	-0.0307	-0.0279	0.0435
UL	-0.0225	-0.0208	0.0584
married			
1 vs 0	-0.1140	-0.0796	0.1936
LL	-0.1188	-0.0838	0.1873
UL	-0.1093	-0.0753	0.1999

Predictions at base value

	1	2	3
Pr(y|base)	0.1282	0.5943	0.2775

- For respondents average on all characteristics, a one-year increase in age is associated with a 0.0003 increase in the probability of being VH, a 0.0001 decrease in PH, and a 0.0001 decrease in NTH
  - Note: NOT sum to 0 because of rounding errors

- Females have a 0.023 greater probability of being VH, 0.01 lower probability of PH, and 0.012 lower probability of NTH compared to males, holding other covariates at their means

Base values of regressors

	age	1. female	1. nonwhite	1. educat	2. educat	1. married
at	46.05	.5578	.1931	.3059	.4656	.5297

Marginal effect at representative values (MER)

```
mchange married, at(married=0 age=40 female=1 nonwhite=0 educat=1)
```

	1	2	3
married			
1 vs 0	-0.110	-0.088	0.198
p-value	0.000	0.000	0.000

Base values of regressors

	age	female	nonwhite	educat	married
at	40	1	0	1	0

- For HS educated, white, 40-year-old, females the probability of VH is 0.198 greater, PH is 0.088 lower, and NTH is 0.11 lower among those who are married compared to those who are not married

```
mchange married, at(married=0 age=40 female=0 nonwhite=0 educat=1)
```

	1	2	3
married			
1 vs 0	-0.119	-0.069	0.188
p-value	0.000	0.000	0.000

Base values of regressors

	age	female	nonwhite	educat	married
at	40	0	0	1	0

- For males with the same characteristics the probability of VH is 0.188 greater, PH is 0.69 lower, and is NTH 0.119 lower among those who are married versus those who are not married

- Note how marginal effects depend on values of Xs

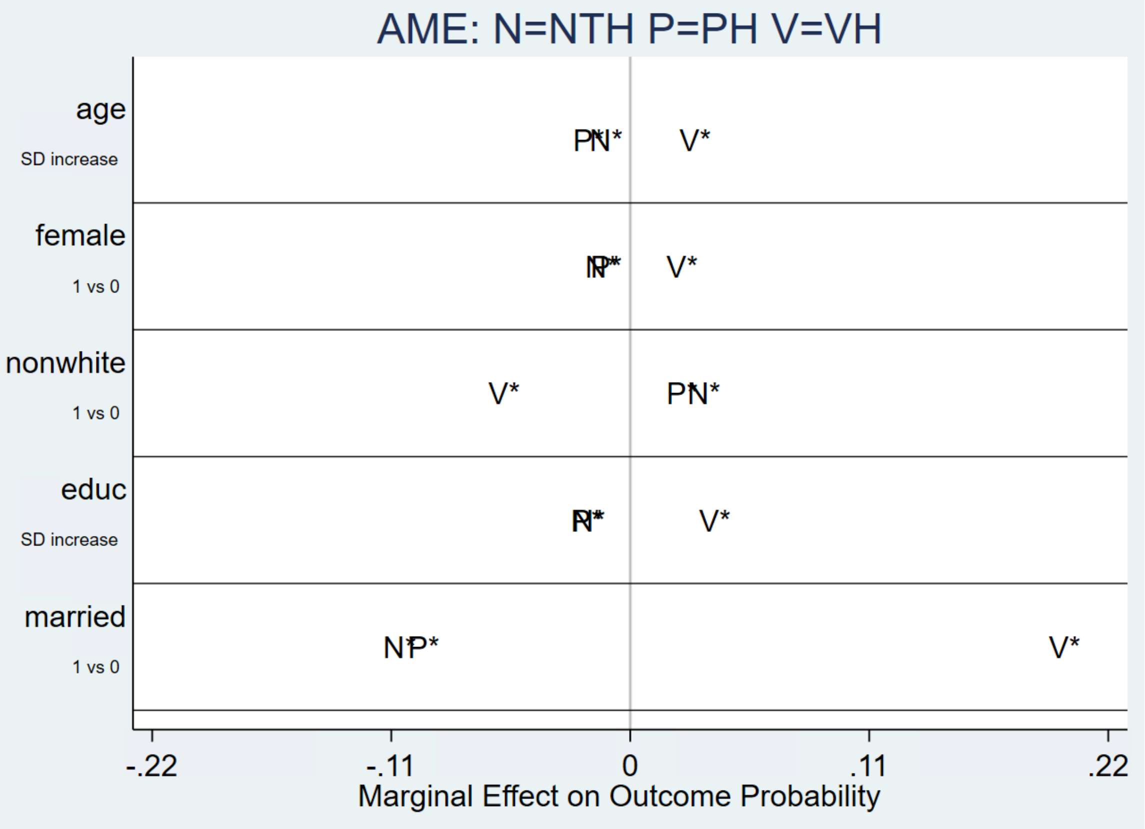
Plotting marginal effects

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

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

	1	2	3
age			
+1	-0.000	-0.000	0.000
p-value	0.137	0.000	0.002
+SD	-0.011	-0.019	0.030
p-value	0.000	0.000	0.000
Marginal	-0.000	-0.000	0.000
p-value	0.440	0.001	0.026
female			
1 vs 0	-0.013	-0.011	0.024
p-value	0.000	0.000	0.000
nonwhite			
1 vs 0	0.034	0.024	-0.058
p-value	0.000	0.000	0.000
educ			
+1	-0.006	-0.006	0.012
p-value	0.000	0.000	0.000
+SD	-0.019	-0.020	0.039
p-value	0.000	0.000	0.000
Marginal	-0.006	-0.006	0.012
p-value	0.000	0.000	0.000
married			
1 vs 0	-0.106	-0.095	0.200
p-value	0.000	0.000	0.000

```
mchangeplot, title("AME: N=NTH P=PH V=VH") symbols(N P V) sig(.05) ///
min(-.22) max(.22)
```



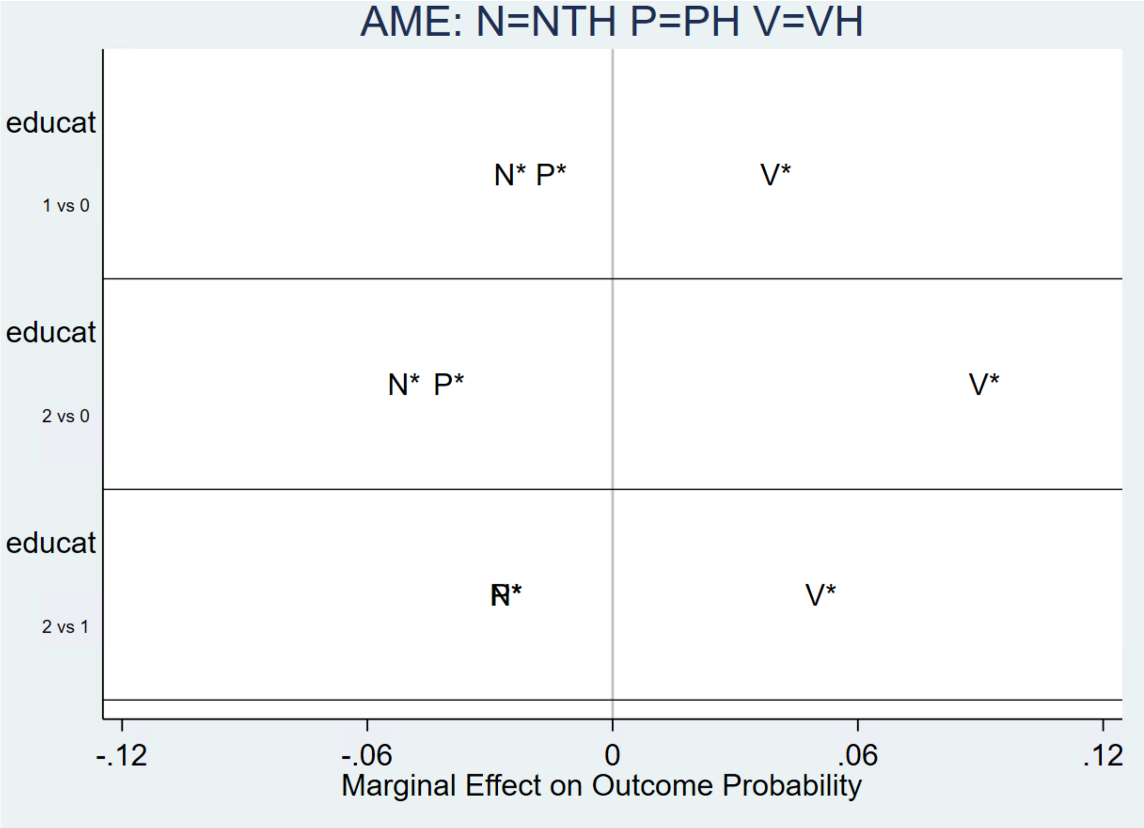
Plotting marginal effects: categorical X

- multiple contrast groups

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

	1	2	3
educat			
1 vs 0	-0.025	-0.015	0.040
p-value	0.000	0.000	0.000
2 vs 0	-0.051	-0.040	0.091
p-value	0.000	0.000	0.000
2 vs 1	-0.026	-0.026	0.051
p-value	0.000	0.000	0.000

```
mchangeplot educat, title("AME: N=NTH P=PH V=VH") symbols(N P V) sig(.05) ///
min(-.12) max(.12)
```



Predicted probabilities: across categorical X

- Predicted probability of happiness by education
  - all else at global means

```
ologit hap c.age##c.age i.female i.nonwhite i.educat i.married if nmiss==0, or
mtable, at(educat=(0 1 2)) atmeans
```

	educat	1	2	3
1	0	0.162	0.612	0.226
2	1	0.136	0.600	0.264
3	2	0.109	0.576	0.315

- The probability of being very happy increases from .23 to .31, while the probability of being not too happy decreases from .16 to .11 when comparing those with >HS to those with <HS education, holding all else at their global means

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

Predicted probabilities: across categorical X

- Predicted probability of happiness by education and race
  - at local means

```
ologit hap c.age##c.age i.female i.nonwhite i.educat i.married if nmiss==0, or
mtable, over(educat nonwhite) atmeans
```

	age	1. female	nonwhite	educat	1. married	1	2	3
1	53.4	.551	0	0	.545	0.149	0.607	0.244
2	48.4	.587	1	0	.36	0.226	0.612	0.162
3	46.2	.59	0	1	.598	0.121	0.588	0.290
4	39.9	.59	1	1	.368	0.190	0.616	0.195
5	44.4	.522	0	2	.555	0.102	0.566	0.332
6	40.2	.599	1	2	.392	0.151	0.608	0.241

- The more you add the more complex to interpret

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

Ideal types

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

```
ologit hap c.age##c.age i.female i.nonwhite c.educ i.married if nmiss==0, or
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	1	2	3
1	0	0	0	0.207	0.615	0.178
2	0	1	0	0.260	0.602	0.139
3	1	0	0	0.188	0.616	0.196
4	1	1	0	0.238	0.609	0.153
5	0	0	1	0.089	0.545	0.366
6	0	1	1	0.116	0.583	0.301
7	1	0	1	0.080	0.526	0.394
8	1	1	1	0.105	0.569	0.326

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

Ideal types: Testing differences

- Let’s compare age 40, male, 12-years education, not married
  - white vs. nonwhite

```
ologit hap c.age##c.age i.female i.nonwhite c.educ i.married if nmiss==0, or
/*store estimates to test with mlincom*/
estimates store olm
/*compare white vs nonwhite with everything else set at same value*/
mlincom, clear
forvalues iout = 1/3 { // start loop
quietly {
mtable, out(`iout') post at(age==40 female==0 educ==12 married==0 nonwhite==0) ///
at (age==40 female==0 educ==12 married==0 nonwhite==1)
mlincom 1-2, stats(est pvalue) rowname(outcome `iout') add
estimates restore olm
}
} // end loop
```

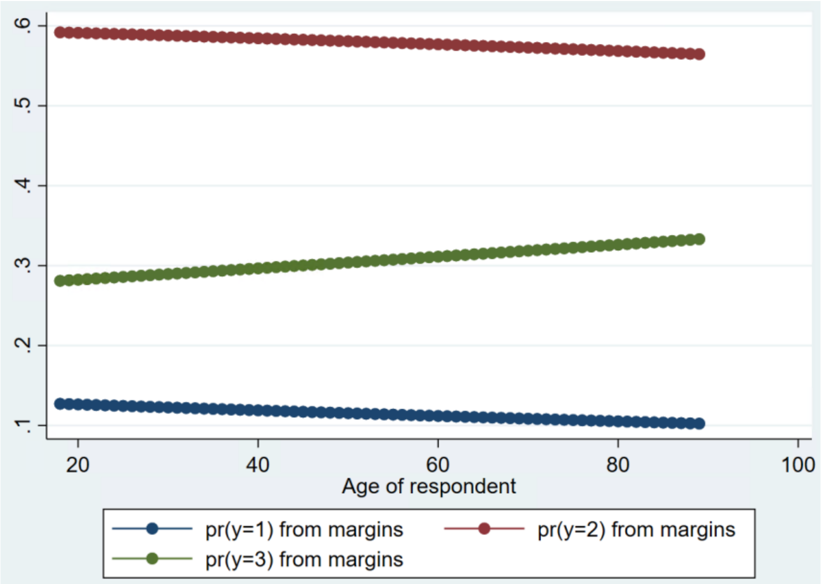
```
mlincom

           |   lincom    pvalue
-----------+--------------------
 outcome 1 |   -0.053     0.000
 outcome 2 |    0.013     0.000
 outcome 3 |    0.039     0.000
```

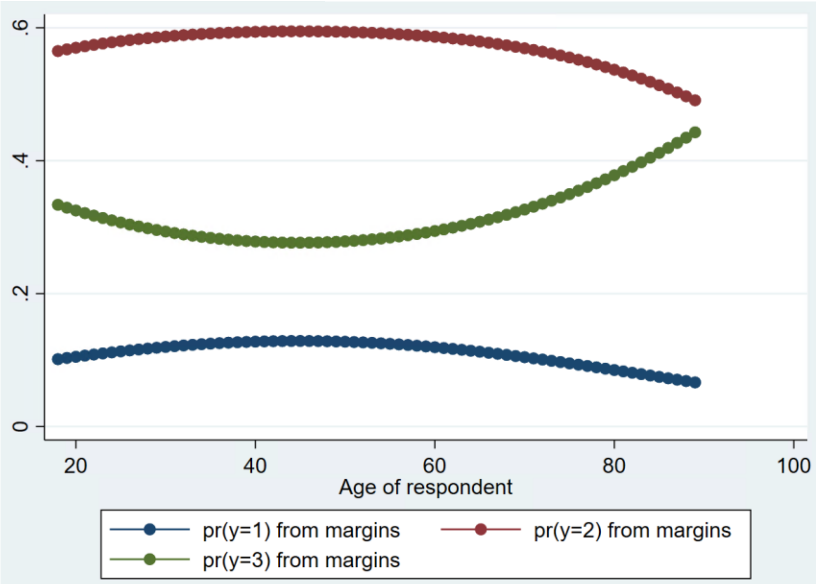
- Recall, postestimation CIs are conservative
- Tests more complex with ologit compared to logit
- I’m okay with using CIs and being more conservative for purposes of this course

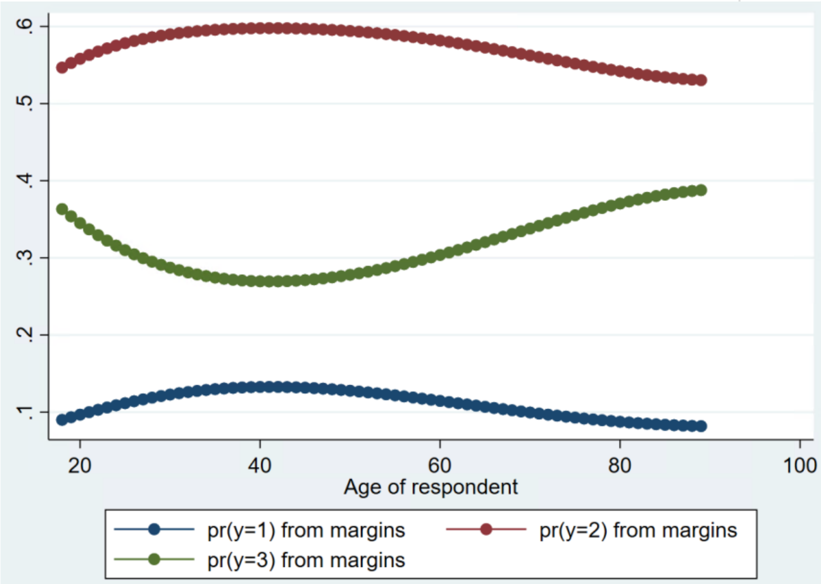
Graphing predicted probabilities: cont. IV

```
ologit hap c.age i.female i.nonwhite c.educ i.married if nmiss==0, or
mgen, at(age=(18(1)89)) atmeans stub(CL5_)
graph twoway connected CL5_pr1 CL5_pr2 CL5_pr3 CL5_age
```

```
ologit hap c.age##c.age##c.age  i.female i.nonwhite c.educ i.married if nmiss==0, or
mgen, at(age=(18(1)89)) atmeans stub(CL2_)
graph twoway connected CL2_pr1 CL2_pr2 CL2_pr3 CL2_age
```



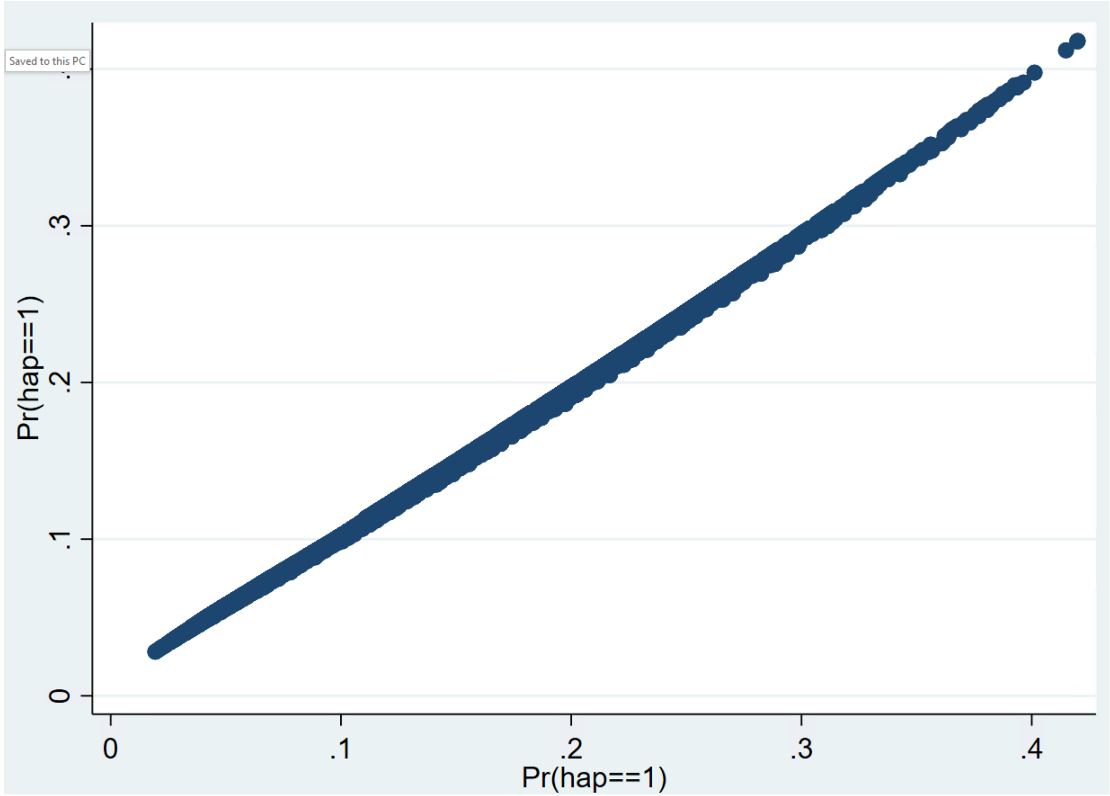





```
ologit hap c.age##c.age i.female i.nonwhite c.educ i.married if nmiss==0, or
mgen, at(age=(18(1)89)) atmeans stub(CL1_)
graph twoway connected CL1_pr1 CL1_pr2 CL1_pr3 CL1_age
```

Ologit vs. oprobit

- Need to rely on predicted probabilities
- Should be almost identical to those from logit
  - if robust




```
ologit hap c.age##c.age i.female i.nonwhite c.educ i.married if nmiss==0, or
predict prologit if nmiss==0
estimates store Aologit
oprobit hap c.age##c.age i.female i.nonwhite c.educ i.married if nmiss==0
predict proprobit if nmiss==0
estimates store Aoprobit
estimates table Aologit Aoprobit /*compare coef*/
scatter prologit proprobit /*compare pred. prob*/
```

Ologit vs. oprobit

- Can use same postestimation techniques
  - except “or”

AME ologit

	1	2	3
age			
+1	-0.0001	-0.0003	0.0003
p-value	0.1368	0.0000	0.0024
+SD	-0.0107	-0.0189	0.0296
p-value	0.0000	0.0000	0.0000
Marginal	-0.0000	-0.0002	0.0002
p-value	0.4404	0.0008	0.0260
female			
1 vs 0	-0.0127	-0.0109	0.0236
p-value	0.0000	0.0000	0.0000
nonwhite			
1 vs 0	0.0338	0.0243	-0.0580
p-value	0.0000	0.0000	0.0000
educ			
+1	-0.0062	-0.0058	0.0121
p-value	0.0000	0.0000	0.0000
+SD	-0.0190	-0.0202	0.0391
p-value	0.0000	0.0000	0.0000
Marginal	-0.0064	-0.0056	0.0120
p-value	0.0000	0.0000	0.0000
married			
1 vs 0	-0.1058	-0.0947	0.2005
p-value	0.0000	0.0000	0.0000

AME oprobit

	1	2	3
age			
+1	-0.0001	-0.0002	0.0002
p-value	0.2282	0.0003	0.0148
+SD	-0.0112	-0.0155	0.0267
p-value	0.0000	0.0000	0.0000
Marginal	-0.0000	-0.0001	0.0002
p-value	0.6182	0.0051	0.0977
female			
1 vs 0	-0.0134	-0.0093	0.0227
p-value	0.0000	0.0000	0.0000
nonwhite			
1 vs 0	0.0360	0.0206	-0.0565
p-value	0.0000	0.0000	0.0000
educ			
+1	-0.0069	-0.0051	0.0120
p-value	0.0000	0.0000	0.0000
+SD	-0.0209	-0.0178	0.0387
p-value	0.0000	0.0000	0.0000
Marginal	-0.0070	-0.0049	0.0119
p-value	0.0000	0.0000	0.0000
married			
1 vs 0	-0.1138	-0.0793	0.1931
p-value	0.0000	0.0000	0.0000

Likelihood ratio (LR) chi-square test

- Test for overall model fit
  - contrasts to model w/ no IVs (constant only)
- Not super informative
  - somewhat useful for nested models

Ordered logistic regression — Number of obs = 59,725; LR chi2(5) = 3887.66; Prob > chi2 = 0.0000; Pseudo R2 = 0.0342

Log likelihood = -54868.981

hap	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.9729281	.0026093	-10.23	0.000	.9678274	.9780556
c.age#c.age	1.000293	.0000266	11.00	0.000	1.00024	1.000345
1.female	1.112681	.0180811	6.57	0.000	1.077801	1.148689
1.nonwhite	.7073297	.0148918	-16.45	0.000	.6787364	.7371276
1.married	2.641215	.0461855	55.54	0.000	2.552226	2.733306

Ordered logistic regression — Number of obs = 59,725; LR chi2(6) = 4384.01; Prob > chi2 = 0.0000; Pseudo R2 = 0.0386

Log likelihood = -54620.805

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

Pseudo-R^2

- Not same as OLS R^2: proportion of explained variance
  - improves likelihood of the model by __% vs. constant-only model

```
Ordered logistic regression                     Number of obs     =     59,725
                                                LR chi2(5)        =    3887.66
                                                Prob > chi2       =     0.0000
Log likelihood = -54868.981                     Pseudo R2         =     0.0342
```

hap	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.9729281	.0026093	-10.23	0.000	.9678274	.9780556
c.age#c.age	1.000293	.0000266	11.00	0.000	1.00024	1.000345
1.female	1.112681	.0180811	6.57	0.000	1.077801	1.148689
1.nonwhite	.7073297	.0148918	-16.45	0.000	.6787364	.7371276
1.married	2.641215	.0461855	55.54	0.000	2.552226	2.733306

```
Ordered logistic regression                     Number of obs     =     59,725
                                                LR chi2(6)        =    4384.01
                                                Prob > chi2       =     0.0000
Log likelihood = -54620.805                     Pseudo R2         =     0.0386
```

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

Information criteria measures

- AIC: Akaike's Information Criteria
- BIC: Bayesian Information Criteria
  - Doesn't matter which one you use, just be consistent

- Smaller → better model fit: BIC rule of thumb
  - 0-2 = no difference between models
  - 2-6 = positive support for model 1
  - 6-10 = strong support
  - > 10 = very strong support

```
ologit hap c.age##c.age i.female i.nonwhite i.married if nmiss==0, or
quietly fitstat, save
/*see how AIC & BIC decreases after adding educ.?*/
ologit hap c.age##c.age i.female i.nonwhite c.educ i.married if nmiss==0, or
fitstat, dif
```

	Current	Saved	Difference
Log-likelihood			
Model	-54620.805	-54868.981	248.176
Intercept-only	-56812.811	-56812.811	0.000
Chi-square			
D(df=59717/59718/-1)	109241.609	109737.962	-496.353
LR(df=6/5/1)	4384.013	3887.660	496.353
p-value	0.000	0.000	0.000
R2			
McFadden	0.039	0.034	0.004
McFadden(adjusted)	0.038	0.034	0.004
McKelvey & Zavoina	0.083	0.074	0.009
Cox-Snell/ML	0.071	0.063	0.008
Cragg-Uhler/Nagelkerke	0.083	0.074	0.009
Count	0.560	0.559	0.001
Count(adjusted)	0.002	-0.001	0.002
IC			
AIC	109257.609	109751.962	-494.353
AIC divided by N	1.829	1.838	-0.008
BIC(df=8/7/1)	109329.589	109814.945	-485.355
Variance of			
e	3.290	3.290	0.000
v-star	3.587	3.551	0.036