

# Models In Epidemiology And Biostatistics

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### Session 11 : Outcomes With More Than Two Levels

# The Distribution of the Outcome

Let us consider a study relating cancer and chemotherapy:

The outcomes were coded: 1=progression of disease, 2=no change, 3=partial remission, 4=complete remission.

The intervention here is 2 types of chemotherapy: 0=sequential, 1=alternating.

It was thought that gender might be a confounder or modifier: 0=male 1=female

## Two 4X2 Tables

If the outcome was dichotomous, we would be considering two 2X2 tables.

Now we will have two 4X2 tables

The conditional probabilities are:  $p_{ijk}$

The probability for the  $i$ th outcome level given the  $j$ th chemotherapy and gender  $k$

# 16 probabilities

## Outcome Level

1      2      3      4

MS       $p_{100}$        $p_{200}$        $p_{300}$        $p_{400}$

MA       $p_{110}$        $p_{210}$        $p_{310}$        $p_{410}$

FS       $p_{101}$        $p_{201}$        $p_{301}$        $p_{401}$

FA       $p_{111}$        $p_{211}$        $p_{311}$        $p_{411}$

The outcome has 4 levels

For example,  $p_{101}$  is, for females, the conditional probability of progression given sequential therapy.

While there are 4 probabilities for each outcome, any 3 determine the fourth since the sum of the 4 probabilities must be one.

$$\sum_{i=0}^4 p_{ijk} = 1 \quad \text{for chemotherapy } j \text{ and gender } k$$

# The data

```
. bysort gender:table therapy outc,col  
-> gender = male
```

therapy		outc			Total
		prog	noch	parrem	
seq		28	45	29	128
alt		41	44	20	125

```
-> gender = female
```

therapy		outc			Total
		prog	noch	parrem	
seq		4	12	5	23
alt		12	7	3	23

## Estimates of probabilities

From this data, we have, for example,

$$\hat{p}_{100} = \frac{28}{128} = 0.21875$$

Notice that:

$$\sum_{i=0}^4 \hat{p}_{ijk} = 1 \quad \text{for chemotherapy } j \text{ and gender } k$$

# Some primitive analysis

```
. tab therapy outc if gender==0,row nofreq exact
```

therapy		outc				Total
		prog	noch	parrem	comrem	
seq		21.88	35.16	22.66	20.31	100.00
alt		32.80	35.20	16.00	16.00	100.00

Fisher's exact = 0.186

```
. tab therapy outc if gender==1,row nofreq exact
```

therapy		outc				Total
		prog	noch	parrem	comrem	
seq		17.39	52.17	21.74	8.70	100.00
alt		52.17	30.43	13.04	4.35	100.00

Fisher's exact = 0.086



# Fisher's Exact Test

For the males, the p-value here is testing the [rather uninteresting] hypothesis:

$$H_0 : p_{i00} = p_{i10} \text{ for } i=1, 2, 3 \text{ and } 4$$

Similarly for the females:

$$H_0 : p_{i01} = p_{i11} \text{ for } i=1, 2, 3 \text{ and } 4$$

# Ignoring gender:

The “crude” analysis would be:

```
. tab therapy outc, row exact
```

therapy	outc				Total
	prog	noch	parrem	comrem	
seq	32	57	34	28	151
	21.19	37.75	22.52	18.54	100.00
alt	53	51	23	21	148
	35.81	34.46	15.54	14.19	100.00
Total	85	108	57	49	299
	28.43	36.12	19.06	16.39	100.00

Fisher's exact = 0.035

## An inadequate analysis

The challenge with such an analysis is that we get no clear indication as to where differences in the conditional probabilities might be. We can describe the estimates and note the omnibus test but most researchers find such an approach too limited and without focus.

## Another approach

Another approach involves pairwise comparisons. One could plan to assess whether improvement [as indicated by outcomes 3 and 4] compared with no improvement [as indicated by outcomes 1 and 2] depends on therapy (...and whether such a comparison is modified or confounded by gender)

BUT... perhaps one should determine whether the collapsing of categories is warranted .

One could:

- a) assess the relationship between therapy and outcomes 1 and 2 given that there was no improvement
- b) assess the relationship between therapy and outcomes 3 and 4 given that there was improvement.

## Is combining OK?

If one were to see an outcome-therapy relationship for either of the focussed assessments [ a) or b) ], then one could note the relationship and argue that the [planned] collapsing would be misleading.

Indeed, to collapse both assumes that there is no relationship seen in either a) or b)

# The 'Classic' Strategy

## Outcome

1

2

3

4

- |    |                              |                |                              |                |
|----|------------------------------|----------------|------------------------------|----------------|
| 1) | compare with 2               | compare with 1 | not included                 | not included   |
| 2) | not included                 | not included   | compare with 4               | compare with 3 |
| 3) | <-----compare with 3&4-----> |                | <-----compare with 1&2-----> |                |

The third assessment could be considered based on the results from the first 2 assessments

## 3 new 'outcomes'

- . gen prog=outc
- . recode prog 1=1 2=0 3=. 4=.
- . gen partial=outc
- . recode partial 1=. 2=. 3=1 4=0
- . gen noimp=outc
- . recode noimp 1=1 2=1 3=0 4=0

Now we have 3 dichotomous outcomes

. cc prog therapy,by(sex)

sex	OR	[95% Conf. Interval]		M-H Weight	
-----+-----					
male	1.497565	.7566925	2.973186	7.797468	(exact)
female	5.142857	.9815142	29.6945	.8	(exact)
-----+-----					
Crude	1.851103	.9974997	3.446361		(exact)
M-H combined	1.836762	1.033281	3.265031		
-----					
Test of homogeneity (M-H)		chi2(1) =	2.29	Pr>chi2 = 0.1301	

Test that combined OR = 1:

Mantel-Haenszel chi2(1) = 4.33  
Pr>chi2 = 0.0374

. cc partial therapy,by(sex)

sex	OR	[95% Conf. Interval]		M-H Weight	
-----+-----					
male	.8965517	.3666776	2.192349	6.105263	(exact)
female	1.2	.0415141	94.09485	.4545455	(exact)
-----+-----					
Crude	.9019608	.3871906	2.104333		(exact)
M-H combined	.9175784	.4199369	2.004944		
-----					
Test of homogeneity (M-H)		chi2(1) =	0.04	Pr>chi2 = 0.8444	

Test that combined OR = 1:

Mantel-Haenszel chi2(1) = 0.05  
Pr>chi2 = 0.8308



## Assessment of the first 2 outcomes

We see that, among those who made no improvement, the odds [of progression cf no change] may be higher for those receiving alternating therapy. Maybe this observation is even more so for the females but the cell numbers are small. In any case, the confidence limits are wide and there is no indication from the testing. For those who made an improvement, the odds ratios could plausibly be one as well.

Not clear cut here, but, if were to then proceed to collapse, recognizing the assumption needed to justify this collapsing, we get:

```
. cc noimp therapy,by(sex)
```

sex	OR	[95% Conf. Interval]		M-H Weight	
-----+-----					
male	1.601027	.9283931	2.766937	11.5415	(exact)
female	2.078125	.4262124	11.34839	1.391304	(exact)
-----+-----					
Crude	1.646578	.9925137	2.737841		(exact)
M-H combined	1.652353	1.020779	2.674693		
-----+-----					
Test of homogeneity (M-H)	chi2(1) =	0.12	Pr>chi2 = 0.7312		

Test that combined OR = 1:

Mantel-Haenszel	chi2(1) =	4.18
	Pr>chi2 =	0.0409

## Based on the collapsing/grouping

If we have made the right call with regard to collapsing, we receive a modest indication of a improvement-therapy relationship.

The odds of no improvement with alternating therapy being estimated to be about 1.65 times the odds of no improvement with sequential therapy

btw... this is a reasonable example of a situation in which it is best if the plan for analysis details [in advance] whether one would consider the crude or adjusted in such a situation

## The process

More importantly, let's review the process here. The outcome has 4 levels. Instead of considering an assessment based on 2 4X2 tables, we tried 3 assessments, each assessment based on 2 2X2 tables. The first 2 assessments were designed to provide support for the third assessment. The third assessment required the assumption that the collapsing into improvement/no improvement did not oversimplify the study of relationship between outcome and therapy.

# A Strategy for Ordinal Outcomes

## Outcome

1

2

3

4

1) compare with 2,3 &4      < -----compare with 1----->

2) < -----compare with 3&4----->      <----- compare with 1&2----->

3) <----- compare with 4----->      compare with 1,2&3

With this strategy, we say that we 'cut' the outcome and consider the 'odds the outcome is greater than the cut'.

'Greater than' and 'Less than' have some merit with ordinal outcomes.

## 3 different odds

The first assessment presents the 'odds the outcome is greater than 1' which here means the 'odds of any outcome except progression'

The second assessment presents the 'odds the outcome is greater than 2' which here means the 'odds of improvement'

The third assessment presents the 'odds the outcome is greater than 3' which here means the 'odds of complete remission'

All 3 assessments are describing the 'odds of doing better' where 'doing better' has 3 versions.

It is sometimes argued that all 3 assessments could be considered. The grouping/collapsing issue is not considered relevant from this point of view.

. cc cut1 therapy,by(sex)

sex	OR	[95% Conf. Interval]		M-H Weight	
male	.5736585	.3137651	1.042641	16.20553	(exact)
female	.1929825	.0374675	.8702495	4.956522	(exact)
Crude	.4820041	.2777758	.8312904		(exact)
M-H combined	.4844976	.2900189	.8093883		

Test of homogeneity (M-H)      chi2(1) =      2.12   Pr>chi2 = 0.1449

Test that combined OR = 1:

Mantel-Haenszel chi2(1) =      7.80  
Pr>chi2 =      0.0052

. cc cut2 therapy,by(sex)

sex	OR	[95% Conf. Interval]		M-H Weight	
male	.6245989	.3614065	1.07715	18.47826	(exact)
female	.481203	.0880998	2.339813	2.891304	(exact)
Crude	.6073201	.3652445	1.007558		(exact)
M-H combined	.6051974	.3738747	.9796435		

Test of homogeneity (M-H)      chi2(1) =      0.12   Pr>chi2 = 0.7312

Test that combined OR = 1:

Mantel-Haenszel chi2(1) =      4.18  
Pr>chi2 =      0.0409

. cc cut3 therapy,by(sex)

sex	OR	[95% Conf. Interval]		M-H Weight	
male	.7472527	.3706607	1.491317	10.79051	(exact)
female	.4772727	.0077437	9.965524	.9565217	(exact)
Crude	.726378	.3709955	1.407016		(exact)
M-H combined	.7252692	.3894278	1.350739		

Test of homogeneity (M-H)      chi2(1) =      0.12   Pr>chi2 = 0.7310

Test that combined OR = 1:

Mantel-Haenszel chi2(1) =      1.02  
Pr>chi2 =      0.3113

# The model specific to each cut

```
. gen gender=sex-1  
. gen gt = gender*therapy  
. gen cut1=(outc>1)  
. gen cut2=(outc>2)  
. gen cut3=(outc>3)  
. logit cut1 gender therapy gt
```

Logistic regression

```
Number of obs   =      299  
LR chi2(3)      =      11.21  
Prob > chi2     =      0.0106  
Pseudo R2      =      0.0314
```

Log likelihood = -172.88277

-----							
cut1		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
gender		.2851767	.5902079	0.48	0.629	-.8716096	1.441963
therapy		-.5557209	.2863726	-1.94	0.052	-1.117001	.0055591
gt		-1.089433	.7475847	-1.46	0.145	-2.554672	.3758063
_cons		1.272966	.213809	5.95	0.000	.8539077	1.692024
-----							



```
. logit cut2 gender therapy gt
```

Logistic regression

```
Number of obs   =      299
LR chi2(3)       =       7.67
Prob > chi2      =      0.0533
Pseudo R2       =      0.0197
```

Log likelihood = -190.57212

cut2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gender	-.5435523	.4870704	-1.12	0.264	-1.498193	.4110882
therapy	-.4706455	.2620022	-1.80	0.072	-.9841604	.0428693
gt	-.2608205	.7593641	-0.34	0.731	-1.749147	1.227506
_cons	-.2831263	.178551	-1.59	0.113	-.6330797	.0668272

```
. logit cut3 gender therapy gt
```

Logistic regression

```
Number of obs   =      299
LR chi2(3)       =       5.80
Prob > chi2      =      0.1219
Pseudo R2       =      0.0217
```

Log likelihood = -130.46941

cut3	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gender	-.984499	.7719356	-1.28	0.202	-2.497465	.5284669
therapy	-.2913518	.3283128	-0.89	0.375	-.934833	.3521294
gt	-.4483152	1.304171	-0.34	0.731	-3.004444	2.107813
_cons	-1.366876	.219694	-6.22	0.000	-1.797469	-.9362839

# The Proportional Odds Model

Now let us consider the probability the outcome is above the cut.  $p_j = \Pr(\text{the outcome is above cut } j)$

Now consider a model of the form:

$$\log(p_j / (1 - p_j)) = \sum_{i=1}^k \beta_i x_i - \kappa_j$$

The  $j$ th assessment is assessed with a logistic model. Each assessment has a possibly different intercept but the rest is the same for each assessment. This is called a proportional odds model because for any 2 assessments  $j$  and  $k$ , say

$$\log(p_j / (1 - p_j)) - \log(p_k / (1 - p_k)) = \kappa_k - \kappa_j$$

Which says that the odds for each assessment  
are proportional

Indeed:  $p_j/(1-p_j) = e^{\kappa_k - \kappa_j} p_k/(1-p_k)$

The constant of proportionality being  $e^{\kappa_k - \kappa_j}$

Indeed, the regression coefficients for the  
explanatory variables are the same for each  
cut. They are 'assumed common' to the cuts.

Suppose we had considered each of these log  
odds with their own model, as before, the odds  
would not be proportional.

Indeed:

3 separate models from before

would look like:

$$\log(p_1/(1-p_1)) = \sum_{i=0}^k \beta_{1i} x_i$$

$$\log(p_2/(1-p_2)) = \sum_{i=0}^k \beta_{2i} x_i$$

$$\log(p_3/(1-p_3)) = \sum_{i=0}^k \beta_{3i} x_i$$

## Difference in Log odds

comparing 1 with 2, for example, would be:

$$\log(p_1/(1-p_1)) - \log(p_2/(1-p_2)) = \sum_{i=0}^k (\beta_{1i} - \beta_{2i}) x_i$$

The difference in log odds would involve the explanatory variables. The odds would not be proportional.

# Test For Proportional Odds

There is a 'goodness of fit' test for the assumption of proportional odds. RF Brant (1990) proposed and developed one such test.

You can download collections of .ado and .do files from Long & Freese (2014). They have developed many macros for numerous forms of analyses of ordinal outcomes.

These commands can be obtained, while in Stata, using 'findit spost13' and following the instructions. In particular:

```
net describe spost13_ado,from(http://www.indiana.edu/~jslsoc/stata)
```

ologit : fits a proportional odds model [o for ordinal]

$$\log(p_j / (1 - p_j)) = \beta_1 G + \beta_2 T + \beta_3 GT - \kappa_j$$

$$\log(\hat{p}_j / (1 - \hat{p}_j)) = b_1 G + b_2 T + b_3 GT - c_j$$

```
. gen gt=gender*therapy
```

```
. ologit outc gender therapy gt
```

Ordered logistic regression

```
Number of obs   =      299
LR chi2(3)      =      11.96
Prob > chi2     =      0.0075
Pseudo R2      =      0.0149
```

Log likelihood = -394.00492

outc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gender	-.2741906	.3873497	-0.71	0.479	-1.033382	.4850008
therapy	-.488071	.2305167	-2.12	0.034	-.9398754	-.0362666
gt	-.5904159	.5791605	-1.02	0.308	-1.72555	.5447177
/cut1	-1.275657	.184367			-1.63701	-.9143045
/cut2	.2957159	.1678283			-.0332216	.6246534
/cut3	1.345164	.1905977			.9715991	1.718728

## The cuts

The cuts are included in this model without a constant term. So, for example, we can see that the log odds of being above cut 1 minus the log odds of being above cut 2 is  $K_2 - K_1$ . This difference is the same for each gender and each therapy. Such differences are 'assumed common' to gender and therapy

This difference is estimated by  $c_2 - c_1$ . Accordingly, this estimate is said to be adjusted for gender and therapy.



## The 'usual' coefficients

For example, a possible interpretation for -0.488071 is, for the males, an estimate of the log odds of 'doing better' with alternating therapy minus the log odds of 'doing better' with sequential therapy.

Here, using the phrase 'doing better' attempts to capture what meant by 'being above' the cut for each cut. We have 'adjusted' for the cuts. The model's regression coefficients are 'assumed common' to the cuts.

# brant : assesses the proportional odds assumption

```
. brant,detail
```

Estimated coefficients from binary logits

Variable	y_gt_1	y_gt_2	y_gt_3
gender	0.285	-0.544	-0.984
	0.48	-1.12	-1.28
therapy	-0.556	-0.471	-0.291
	-1.94	-1.80	-0.89
gt	-1.089	-0.261	-0.448
	-1.46	-0.34	-0.34
_cons	1.273	-0.283	-1.367
	5.95	-1.59	-6.22

legend: b/t

<- b is the estimated regression coefficient

<- t is the Wald z statistic

Brant test of parallel regression assumption

	chi2	p>chi2	df
All	3.75	0.711	6
gender	2.28	0.320	2
therapy	0.59	0.745	2
gt	1.00	0.607	2

# Interpreting the 'Brant' test

The command, 'brant' comes from the materials accompanying the book by Long and Freese.

The output provides the estimated regression coefficients [and the Wald z statistics] from the 3 separate 'ordinary' logistic regressions. One can assess their differences qualitatively.

Then, we get an omnibus test with 6 degrees of freedom made up of the three 2 degree of freedom tests.

Each 2 degree of freedom test comparing one set of the 3 regression coefficients associated with a given explanatory variable.

# A complete assessment of therapy and gender

Just like with logistic regression, we can use a proportional odds model to assess gender as a modifier, then, if there is no evidence of modification, assess gender as a confounder and then discuss the outcome-therapy relationship using the 3 ologit commands.

Here, we see that gender neither modifies or confounds. Further, this method has detected evidence of an outcome-therapy relationship ( $p=0.007$ ). The estimated log odds ratio is  $-0.5699$  and so the estimated odds ratio is  $\exp(-0.5699)=0.5656$  and so the odds of doing better for those receiving alternating is  $0.5656$  the odds of doing better with sequential.

```
. ologit outc gender therapy
```

Ordered logistic regression

```
Number of obs   =      299
LR chi2(2)       =      10.91
Prob > chi2      =      0.0043
Pseudo R2       =      0.0136
```

Log likelihood = -394.52832

outc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
gender	-.5413938	.2871816	-1.89	0.059	-1.104259	.0214717
therapy	-.580685	.2121478	-2.74	0.006	-.996487	-.164883
-----+-----						
/cut1	-1.318043	.1797769			-1.670399	-.9656869
/cut2	.2492335	.1613881			-.0670813	.5655484
/cut3	1.300056	.1849928			.9374766	1.662635
-----+-----						

```
. ologit outc therapy
```

Ordered logistic regression

```
Number of obs   =      299
LR chi2(1)       =       7.31
Prob > chi2      =      0.0068
Pseudo R2       =      0.0091
```

Log likelihood = -396.32657

outc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
therapy	-.5699142	.2117716	-2.69	0.007	-.9849789	-.1548495
/cut1	-1.21673	.1704333			-1.550773	-.8826866
/cut2	.3382206	.1542139			.035967	.6404743
/cut3	1.380296	.1801627			1.027184	1.733409

# Fitted Values : On the Log Odds Scale

The fitted values are determined with the cuts set to zero :

$$\log(\hat{p}_j / (1 - \hat{p}_j)) = b_1 G + b_2 T + b_3 GT$$

```
. predict lo,xb  
. predict selo,stdp  
. table gender therapy,c(mean lo mean selo)
```

-----			
gender		therapy	
		seq	alt
-----			
m		0	-.488071
		0	.2305167
f		-.2741906	-1.352677
		.3873497	.4322978
-----			

# Cut specific fitted values : the comparisons are the same for each cut

```
. gen loc1 = lo + 1.275657  
. gen loc2 = lo - 0.2957159  
. gen loc3 = lo - 1.345164
```

therapy			
gender	seq	alt	alt - seq
cut 1			
0	1.275657	.787586	-0.488071
1	1.001466	-.0770205	-1.078486
cut 2			
0	-.2957159	-.7837869	-0.488071
1	-.5699065	-1.648393	-1.078486
cut 3			
0	-1.345164	-1.833235	-0.488071
1	-1.619355	-2.697841	-1.078486

## Fitted Values: Estimates of probabilities for each outcome level

We can determine:

$$\begin{aligned} Pr(Y = j) &= Pr(Y > j-1) - Pr(Y > j) \\ &= \frac{1}{1 + e^{-(\beta_1 G + \beta_2 T + \beta_3 GT - \kappa_{j-1})}} - \frac{1}{1 + e^{-(\beta_1 G + \beta_2 T + \beta_3 GT - \kappa_j)}} \\ &= \frac{1}{1 + e^{(\kappa_{j-1} - \beta_1 G - \beta_2 T - \beta_3 GT)}} - \frac{1}{1 + e^{(\kappa_j - \beta_1 G - \beta_2 T - \beta_3 GT)}} \end{aligned}$$

where we pretend that  $\kappa_0 = -\infty$  and  $\kappa_4 = \infty$



# Specify one variable for each outcome level

```
predict p1h p2h p3h p4h
(option pr assumed; predicted probabilities)

. table gender therapy,c(mean p1h mean p2h mean p3h mean p4h)
```

```
-----
      |      therapy
gender |      seq      alt
-----+-----
      |
m      | .2182904 .3126872
      | .3551045 .3738085
      | .2199429 .1756509
      | .2066622 .1378534
      |
f      | .2686532 .5192456
      | .3700884 .3194282
      | .1959645 .0982254
      | .1652939 .0631009
```

For example, the estimate of the probability of progression for women receiving alternating therapy is 0.5192456

# What to do if there is evidence against proportional odds

There are several options :

- 1) Develop and fit the separate cut specific models [logit]
- 2) Develop and fit models that do not make the proportional odds assumption : sometimes called Generalized Proportional Odds Models or Generalized Ordered Logit Models [available with gologit2 added to Stata]
- 3) Develop and fit models that assume proportional odds for some [but not all] explanatory variables and not for the remaining explanatory variables : sometimes called Partial Proportional Odds Models [gologit2 in Stata]
- 4) Consider 'Multinomial' Models [next]

# The Multinomial Logit Model

Now let us consider a model to analyze outcomes with assumed nominal levels (i.e. not necessarily ordinal levels). There is a set of models called multinomial logit models (also sometimes called polytomous logistic regressions) (available in Stata using `mlogit`).

Here, one selects a baseline 'level' of the outcome and then constructs comparisons between each of the other levels with the baseline level (one-at-a-time).

The model looks like...

...the following:  $\log(p_j/p_{BL}) = \sum \beta_{ij} x_i$

where  $p_j$  is now  $\Pr(\text{outcome} = \text{level } j)$  where  $p_{BL}$  is the probability of the baseline outcome.

the  $\beta_{ij}$  have the usual interpretations except that now we now have phrases like “ a difference between the log rate ratio with exposure minus the log rate ratio without exposure” or the “rate of change of the log of the rate ratio per year in age”

Note: these ratios are not odds ratios

## Relative Risk Ratios

The exponents (  $\exp(\beta_{ij})$  ) are sometimes called “relative risk ratios” (ouch!) in so far as they can be ratios of risk ratios (of course, we can have ratios of ratios of risk ratios etc...)

Let us now try mlogit with our tumor study:

(By default, mlogit uses the most frequent outcome level as baseline: here outc=2 (noch) is the most frequent and becomes baseline.

There is an option to change this default level :  
baseoutcome(number) )

```
. mlogit outc gender therapy gt
```

Multinomial logistic regression

Number of obs = 299

LR chi2(9) = 16.48

Prob > chi2 = 0.0575

Log likelihood = -391.74448

Pseudo R2 = 0.0206

-----		outc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	-----	
prog									
	gender		-.6241543	.6255157	-1.00	0.318	-1.850142	.6018339	
	therapy		.4038404	.3241204	1.25	0.213	-.2314239	1.039105	
	gt		1.233768	.8152164	1.51	0.130	-.3640265	2.831563	
	_cons		-.474458	.2407	-1.97	0.049	-.9462214	-.0026946	
noch			(base outcome)						
parrem									
	gender		-.4361021	.583128	-0.75	0.455	-1.579012	.7068079	
	therapy		-.3490907	.3597669	-0.97	0.332	-1.054221	.3560396	
	gt		.3772616	.9428447	0.40	0.689	-1.47068	2.225203	
	_cons		-.4393667	.2381281	-1.85	0.065	-.9060891	.0273558	
comrem									
	gender		-1.243194	.8025068	-1.55	0.121	-2.816078	.3296908	
	therapy		-.2398914	.3652548	-0.66	0.511	-.9557776	.4759947	
	gt		.0857433	1.363671	0.06	0.950	-2.587003	2.75849	
	_cons		-.548566	.2463407	-2.23	0.026	-1.031385	-.065747	

```
. mlogit outc gender therapy
```

Multinomial logistic regression

Number of obs = 299

LR chi2(6) = 13.93

Prob > chi2 = 0.0304

Log likelihood = -393.01778

Pseudo R2 = 0.0174

-----		outc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----							
prog							
	gender		.0902263	.37863	0.24	0.812	-.6518748 .8323275
	therapy		.6164509	.2954663	2.09	0.037	.0373475 1.195554
	_cons		-.5941062	.2320624	-2.56	0.010	-1.04894 -.1392722
-----+-----							
noch			(base outcome)				
-----+-----							
parrem							
	gender		-.2716142	.4580482	-0.59	0.553	-1.169372 .6261438
	therapy		-.2814293	.3319521	-0.85	0.397	-.9320435 .3691849
	_cons		-.4731007	.2281474	-2.07	0.038	-.9202614 -.0259401
-----+-----							
comrem							
	gender		-1.188069	.6474476	-1.84	0.067	-2.457043 .0809049
	therapy		-.182163	.3491509	-0.52	0.602	-.8664862 .5021603
	_cons		-.5776952	.2388478	-2.42	0.016	-1.045828 -.1095621
-----+-----							

```
. mlogit outc therapy
```

Multinomial logistic regression

Number of obs = 299

LR chi2(3) = 8.69

Prob > chi2 = 0.0338

Log likelihood = -395.6413

Pseudo R2 = 0.0109

outc		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
prog							
	therapy	.6157816	.2954143	2.08	0.037	.0367802	1.194783
	_cons	-.5773153	.2208933	-2.61	0.009	-1.010258	-.1443724
noch		(base outcome)					
parrem							
	therapy	-.2796407	.3317254	-0.84	0.399	-.9298105	.3705291
	_cons	-.5166907	.2166925	-2.38	0.017	-.9414002	-.0919813
comrem							
	therapy	-.1764564	.3471095	-0.51	0.611	-.8567786	.5038658
	_cons	-.7108468	.2307773	-3.08	0.002	-1.163162	-.2585316



## Interpreting mlogit

Since there are four levels of outc, there are, for each candidate model, 3 sets of regression coefficients.

As with logit and ologit, one can use mlogit to address modification, confounding and outcome-exposure issues although the assessment has the added complexity of the multiple sets of coefficients.

The option 'rrr' takes the exponent of the coefficients which can yield 'relative risk ratios' or ratios of ratios [as elsewhere]

For example

No modification or confounding to be noted

Here, we can see little of material interest in the 2 rate ratios:

: partial remission relative to no change

: complete remission relative to no change

Regarding the outcome: progression relative to no change, we do see an outcome-therapy relationship.

## Progression of disease

Since  $\exp(0.6157816)=1.8511029$ , we can note that the progression rate relative to the 'no change' rate for those receiving alternating chemotherapy is estimated to be 1.85 times the progression rate relative to the 'no change' rate for those receiving sequential chemotherapy.

Notice that this is a much more focussed statement about the nature of the outcome-therapy relationship than that obtained from ologit.

# Fitted Values: Log Rate Ratio Scale

The fitted values on the log rate ratio scale are determined for all but the baseline:

$$A_j = \log \hat{p}_j - \log \hat{p}_2 = b_{0j} + b_{1j}G + b_{2j}T + b_{3j}GT$$

```
. quietly: mlogit outc gender therapy gt  
  
. predict lo1h,xb outcome(1)  
  
. predict lo2h,xb outcome(2)  
  
. predict lo3h,xb outcome(3)  
  
. predict lo4h,xb outcome(4)
```

# A table of fitted values

```
. table g t,c(m lo1h m lo2h m lo3h m lo4h)
```

-----		
		t
g		0 1
-----+-----		
0		-.474458 -.0706176
		0 0
		-.4393667 -.7884573
		-.5485659 -.7884573
1		-1.098612 .5389965
		0 0
		-.8754687 -.8472978
		-1.791759 -1.945908
-----		

So, for example, for men receiving sequential therapy, the log of the complete remission rate minus log of the 'no change' rate is estimated to be -0.5485659

## Fitted Values: Probability Scale

We have:  $\frac{p_j}{p_2} = e^{A_j}$  and  $\sum_{i=1}^4 p_i = 1$

$$p_1 = p_2 e^{A_1} \quad p_3 = p_2 e^{A_3} \quad p_4 = p_2 e^{A_4}$$

$$p_1 + p_3 + p_4 = p_2 (e^{A_1} + e^{A_3} + e^{A_4})$$

$$1 - p_2 = p_2 (e^{A_1} + e^{A_3} + e^{A_4})$$

$$p_2 = \frac{1}{(1 + e^{A_1} + e^{A_3} + e^{A_4})}$$

# Stata does the work

```
. quietly: mlogit outc gender therapy gt  
  
. predict p1h p2h p3h p4h  
  
. table g t, c(m p1h m p2h m p3h m p4h)
```

-----		
		t
g		0 1
-----		
0		.21875 .328
		.3515625 .352
		.2265625 .16
		.203125 .16
1		
		.173913 .5217391
		.5217391 .3043478
		.2173913 .1304348
		.0869565 .0434784
-----		

For example, the estimate of the probability of progression for women receiving alternating therapy is 0.5217391

# Reverse coding the outcome

Indeed, if we reverse the order:

```
. gen outcw=5-outc
```

```
. table outcw outc
```

-----				
outcw		outc		
		prog	noch	parrem comrem
-----				
1				49
2				57
3			108	
4		85		
-----				



```
. ologit outcw therapy
Ordered logistic regression
```

```
Number of obs   =      299
LR chi2(1)      =      7.31
Prob > chi2     =      0.0068
Pseudo R2      =      0.0091
```

```
Log likelihood = -396.32657
```

outcw	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
therapy	.5699142	.2117716	2.69	0.007	.1548495	.9849789
/cut1	-1.380296	.1801627			-1.733409	-1.027184
/cut2	-.3382206	.1542139			-.6404743	-.035967
/cut3	1.21673	.1704333			.8826866	1.550773

```
. disp exp(0.5699142)
1.7681153
```

```
. brant,detail
Estimated coefficients from j-1 binary regressions
```

```
          y>1          y>2          y>3
therapy   .3196848   .49869928   .72980261
_cons     1.4799798   .36150198  -1.3133876
```

```
Brant Test of Parallel Regression Assumption
```

Variable	chi2	p>chi2	df
All	1.38	0.503	2
therapy	1.38	0.503	2

ologit then presents 'odds of doing worse'

From the previous ologit:

: the odds of doing worse with alternating chemotherapy is estimated to be 1.77 times the odds of doing worse with sequential chemotherapy

Reverse coding has no effect on mlogit:

```
. mlogit outcw therapy
```

Multinomial logistic regression	Number of obs	=	299
	LR chi2(3)	=	8.69
	Prob > chi2	=	0.0338
Log likelihood = -395.6413	Pseudo R2	=	0.0109

outcw		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1							
	therapy	-.1764564	.3471095	-0.51	0.611	-.8567786	.5038658
	_cons	-.7108468	.2307773	-3.08	0.002	-1.163162	-.2585316
2							
	therapy	-.2796407	.3317254	-0.84	0.399	-.9298105	.3705291
	_cons	-.5166907	.2166925	-2.38	0.017	-.9414002	-.0919813
3		(base outcome)					
4							
	therapy	.6157816	.2954143	2.08	0.037	.0367802	1.194783
	_cons	-.5773153	.2208933	-2.61	0.009	-1.010258	-.1443724

outcw does not have labels for the codes:  
progression is now outcw=4