

The Analysis of Ordinal Data with Graphs and Odds Ratios

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Outline

Ordinal Logistic Regression Models

- Cumulative Logit
- Checking the Proportional Odds Assumption
- Adjacent Logit
- Odds Ratios
- Predicted Probabilities
- Visual Displays

Power Analysis with Ordered Categories



Ordinal Data

Categorical Data with an Inherent Order

Responses that reflect an ordered progression from the lowest to highest (or highest to lowest) levels in succession without reversing trend

Evaluate responses difficult or impossible to quantify, qualitative or “subjective” endpoints, such as:

- Levels of agreement or disagreement
- Behavior (frequency of activity)
- Perceived difficulty of a task
- Sensation of pain
- Medical tests
 - Gleason: $\leq 6, 7, 8, 9, 10$ (range is 2-10, typically recorded 6-10 or grade divided into three groups: $\leq 6, 7, 8-10$)
 - PI-RADS: 1,2,3,4,5 (measures how likely cancer is present)

Coding actual numbers into ordinal categories is generally NOT recommended for data analysis purposes



Coding Ordinal Data

Order Matters

Default settings of SAS procedures interpret character data or variables in a CLASS statement (discrete) are sorted in increasing order

- Alphabetical: a b c d e ..
- Numerical: 1 2 3 .. k

Where to start: ascending order

- Code ordinal data response level of "greatest" interest as 1 with increasing integers for remaining levels
- Contrast with binary data coded as 0/1

Assign actual values of numerical data codes with a format

```
PROC FORMAT;
```

```
VALUE rsp 1='Never' 2='Rarely' 3='Sometimes' 4='Often' 5='Always';
```

```
VALUE rspA 1='a Never' 2='b Rarely' 3='c Sometimes' 4='d Often' 5='e Always';
```

```
RUN;
```

Apply order= option when displaying data:

```
order = internal ( with rsp )
```

```
order = formatted ( with rspA )
```



Coding Data Preferences for Analysis (especially important with ordinal data)

All Data

- Define with short variable names (acronyms) and assign labels

Categorical Data

- Code with integers or short character of same length and case (some macros require all numbers)
- Numerical or alphabetical order matters
- Assign actual values with formats

General recommendations for data analysis:

- Do not assign formats to data in the DATA step
- When making data sets with ODS options, analyze data in procedures without FORMAT statements
- Apply FORMATS within the various SAS procedures that print or display the desired printed results



Analysis of Ordinal Data

Ordinal nature of outcome data much too often ignored

Ordinal data as a subjective measurement of an attribute, e.g., 2 is larger than 1, 3 is larger than 2, etc., yet how much numerically is not well-defined

Reduce k ordinal levels to 2 or 3 levels

- Apply only if small cell counts present

Analyze as continuous/interval data (treat as numbers)

- Resort to t-tests, ANOVA, regression methods often a matter of convenience for a "quicker, simpler" interpretation

Preferred approach is to summarize with odds ratios and predicted probabilities displayed in tables and graphs



SAS Software Procedures

Statistical Procedures with MODEL statement options

```
PROC LOGISTIC / link = clogit < alogit > unequalslopes
```

Procedures not discussed, available as needed

```
PROC GENMOD / dist=multinomial link = cumlogit
```

```
PROC GLIMMIX / dist=multinomial link = cumlogit
```

```
PROC NLMIXED
```

```
PROC CATMOD
```

Make Visual Displays

```
PROC SGPLOT
```

```
PROC SGPANEL
```

```
PROC PLOT (rough graphs for diagnostic purposes)
```

Utility Procedures

```
PROC TABULATE
```

```
PROC FREQ
```

```
PROC FORMAT
```

```
PROC TRANSPOSE
```

```
PROC MODEL (ETS)
```



Binary Logistic Regression

	a Yes	b No	Odds	Odds Ratio
a Treatment	p11	p12	odds1 = $p11 / p12$	OR = $odds1 / odds2$
b Control	p21	p22	odds2 = $p21 / p22$	

Data summarized as row percents in a 2x2 table

$p11 > p21$ implies odds ratio will be > 1

Columns: outcome

Primary level of interest placed in column 1

Rows: treatment

Reference category (Control) placed in row 2

Row probabilities sum to 1

In SAS enter:

```
PROC FREQ DATA= inpdatt order=formatted;
TABLE x * y / nocol nopercnt cmh2;
FORMAT x trt. y ysn. ;
RUN;
```



Ordinal Logistic Regression with $k=4$ levels

	1=Very Good	2=Good	3=Moderate	4=Poor	Sum
a Treatment	p11	p12	p13	p14	1.0
b Control	p21	p22	p23	p24	1.0

Response has k discrete categories (usually 3 to 5 levels)

Make a $2 \times k$ table ($k=4$ in table above)

Columns: ordinal outcome
level of primary interest in column 1

Rows: Treatment vs Control
Reference category in bottom row (row 2)

Row probabilities, p_{ij} , sum to 1 for $i = 1, 2$



Ordinal Logistic Regression with k=4 levels

Choose ascending or descending order of the response



	1=Very Good	2=Good	3=Moderate	4=Poor
a Treatment	p11	p12	p13	p14
b Control	p21	p22	p23	p24

The objective is to compute the odds ratio(s) and predicted probabilities based on one of two methods of grouping the ordinal responses (ascending or descending) with two types of link functions

Cumulative logit

Adjacent logit



Response Profile: Ascending

```
ODS select responseprofile;  
PROC LOGISTIC DATA=indat ; * default is ascending levels for the response;  
MODEL y = x1 x2;  
RUN;
```

Response Profile

Ordered Value	y	Total Frequency
1	1	60
2	2	42
3	3	21
4	4	14

Probabilities modeled are cumulated over the lower Ordered Values.

Computed over lower order values in this setting means having these odds:

$$\begin{array}{l} \text{[Prob(y=1)] / [Prob(y=2) + Prob(y=3) + Prob(y=4)]} \\ \text{[Prob(y=1) + Prob(y=2)] / [Prob(y=3) + Prob(y=4)]} \\ \text{[Prob(y=1) + Prob(y=2) + Prob(y=3)] / [Prob(y=4)]} \end{array}$$


Response Profile: Descending

```
ODS select responseprofile;  
PROC LOGISTIC DATA=indat descending;  
MODEL y = x1 x2;  
RUN;
```

Response Profile

Ordered Value	y	Total Frequency
1	4	14
2	3	21
3	2	42
4	1	60

Probabilities modeled are cumulated over the lower Ordered Values.

Computed over lower order values in this setting means having these odds:

$$\begin{aligned} & \left[\text{Prob}(y=4) \right] / \left[\text{Prob}(y=3) + \text{Prob}(y=2) + \text{Prob}(y=1) \right] \\ & \left[\text{Prob}(y=4) + \text{Prob}(y=3) \right] / \left[\text{Prob}(y=2) + \text{Prob}(y=1) \right] \\ & \left[\text{Prob}(y=4) + \text{Prob}(y=3) + \text{Prob}(y=2) \right] / \left[\text{Prob}(y=1) \right] \end{aligned}$$


Ordinal Logistic Regression: Cumulative Logit

	1 Very Good	2 Good	3 Moderate	4 Poor
Treatment	p11	p12	p13	p14
Control	p21	p22	p23	p24

Cumulative logit

Probabilities summed across all four response levels

Row T: $\text{odds}_T = A / B$

Row C: $\text{odds}_C = C / D$

Where components A, B, C, D defined for the first comparison

Compare (Very Good) to (Good, Moderate, Poor)

T: $\text{odds}_{11} = (p_{11} \quad) / (p_{12} + p_{13} + p_{14})$

C: $\text{odds}_{21} = (p_{21} \quad) / (p_{22} + p_{23} + p_{24})$



Ordinal Logistic Regression: Cumulative Logit

Cumulative logit

Probabilities summed across all four response levels

$$\begin{array}{lcl} \text{Treatment:} & \text{odds T} & = \quad A \quad / \quad B \\ \text{Control:} & \text{odds C} & = \quad C \quad / \quad D \end{array}$$

With k=4 have three ways to write pairs of equations for the odds

$$\begin{array}{lcl} \text{T: odds11} & = (p_{11} &) / (p_{12} + p_{13} + p_{14}) \\ \text{C: odds21} & = (p_{21} &) / (p_{22} + p_{23} + p_{24}) \end{array}$$

$$\begin{array}{lcl} \text{T: odds12} & = (p_{11} + p_{12} &) / (p_{13} + p_{14}) \\ \text{C: odds22} & = (p_{21} + p_{22} &) / (p_{23} + p_{24}) \end{array}$$

$$\begin{array}{lcl} \text{T: odds13} & = (p_{11} + p_{12} + p_{13}) & / (p_{14}) \\ \text{C: odds23} & = (p_{21} + p_{22} + p_{23}) & / (p_{24}) \end{array}$$

Cumulative Proportional Odds Model

Three equations of predicted values all compute one odds ratio

$$\text{Odds ratio} = \frac{\text{Odds T}}{\text{Odds C}} = \frac{(A / B)}{(C / D)}$$



Checking the Proportional Odds Assumption

A recent SAS resource with examples

Usage Note 37944

Plotting empirical (observed) logits for
binary and ordinal response data

<https://support.sas.com/kb/37/944.html>

Page also has a link to download the

CtoN.sas macro

(character to numeric)



Ordinal Logistic Regression

Checking the proportional odds condition

PROC LOGISTIC

Score Test for the Proportional Odds Assumption

Visual aids

SAS Global Forum 2013 Paper 446-2013

Ordinal Response Modeling with the LOGISTIC Procedure
Bob Derr, SAS Institute Inc.

www.lexjansen.com

Search for "proportional odds"

Download pdf file for 446-2013

Direct link to the macros is found on page 11

<http://support.sas.com/rnd/app/stat/papers/aastaffcode2013.html>



Graphical Assessment of proportional odds



SUPPORT

RESOURCES / FOCUS AREAS

FOCUS AREAS

- ▀ Base SAS
- ▀ Graphics
- ▀ Enterprise Management Integration
- ▀ Migration
- ▀ Scalability & Performance
- ▀ SAS for Containers
- ▀ Statistics & Operations Research
 - SAS/ETS
 - SAS/IML
 - SAS/OR
 - SAS/QC
 - SAS/STAT

Programs Referenced in 2013 SAS Global Forum Papers

Ordinal Response Modeling with the LOGISTIC Procedure

By Bob Derr

- [LRTest Macro](#)
- [LRTestCycle Macro](#)

- [OneClassPlot Macro](#)
- [OneContPlot Macro](#)
- [EmpiricalLogitPlot Macro](#)
- [EXPlot Macro](#)

Does the addition of variables improve model? (unequalslopes option included)

Macros which produce graphical displays of the proportional odds assumption



Hints to Run the Macros

- All explanatory variables must be numeric (early version need to dummy code categorical data before submitting macros, except the two LRT macros)
- Ordinal response coded from 1 to k [1,2, ..., k]
- Submit file with individual observations (frequency indicated by a "count" variable not available)
- May want to modify the SGPlot and SGPANEL options, especially graph dimensions and display options, and what folder to store it
- Data sets merged without a BY statement; macros will not work with this option:

```
OPTIONS mergeNoBy=error;
```

Change to

```
OPTIONS mergeNoBy=warn;
```



Plots evaluate proportional odds in two ways

Empirical Logit Plot

ELP: Plots the empirical logits against observed X values (all coded as numeric), one at a time, unadjusted models

Are the plotted lines parallel?

EXPlot

EXP: Compares the mean of the X variable within each level of Y, to the expected value of $X|Y=j$ given that the proportional odds assumption holds, $E(X|Y=j)$, $j = 1, 2, \dots k$
From Harrell (2001, 2015).

Do the two lines follow the same trajectory?



Proportional Odds Assumption

Which table can be evaluated with one odds ratio?

Table 1	1	2	3	4	5	Total
Treatment	86	48	30	21	15	200
	.43	.24	.15	.105	.075	1.0
Control	40	40	40	40	40	200
	.2	.2	.2	.2	.2	1.0

Table 2	1	2	3	4	5	Total
Treatment	86	55	9	24	26	200
	.43	.275	.045	.12	.13	1.0
Control	40	40	40	40	40	200
	.2	.2	.2	.2	.2	1.0



Table 1 Summary

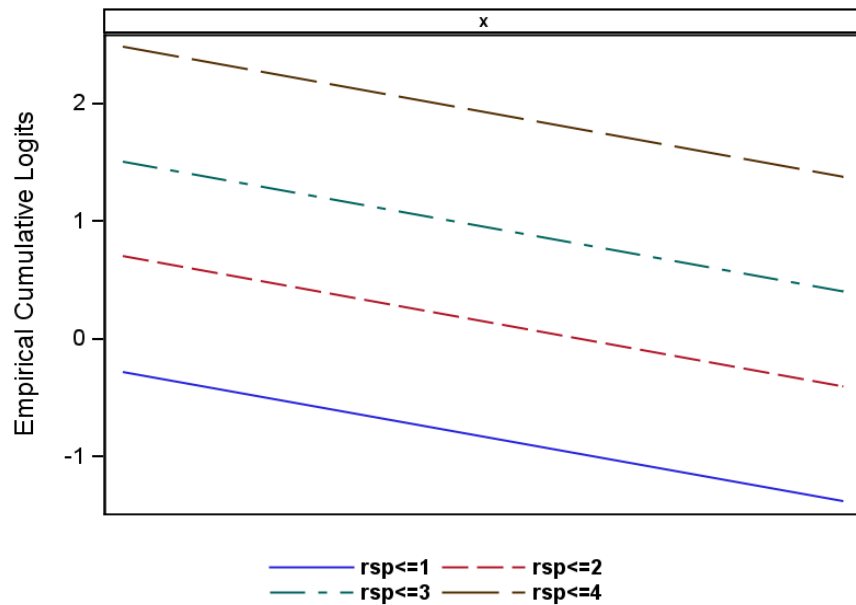
Score Test for the Proportional Odds Assumption

Chi-Square
0.0059

DF
3

Pr > ChiSq
0.9999

Empirical Cumulative Logit Plots



Ratio of mean of X within each level of Y,
to the expected value of $X|Y=j$

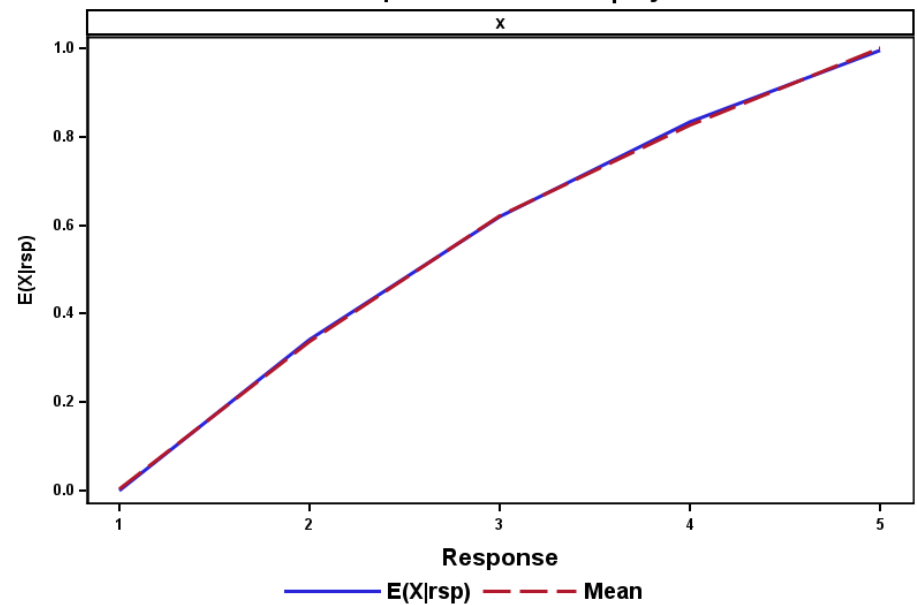
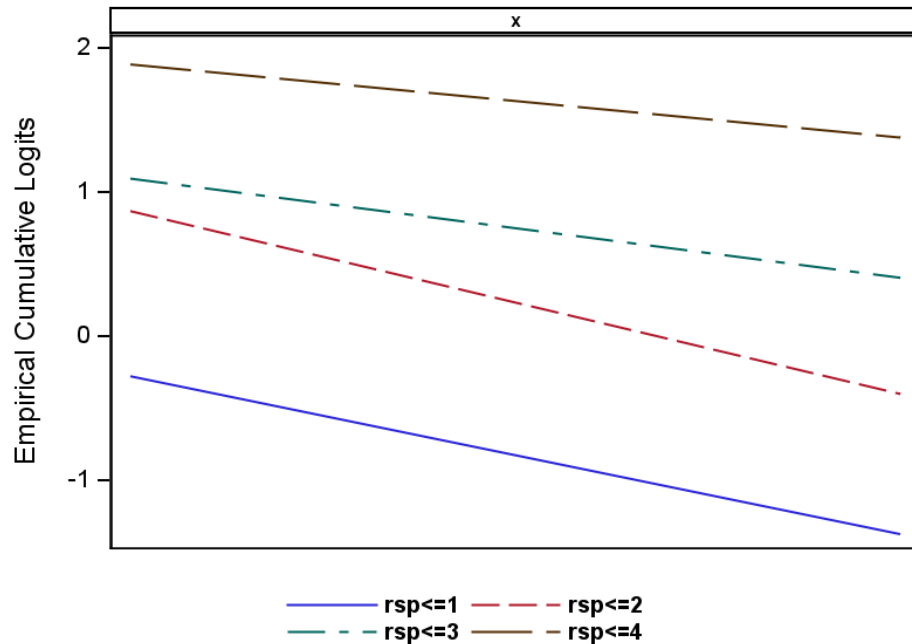


Table 2 Summary

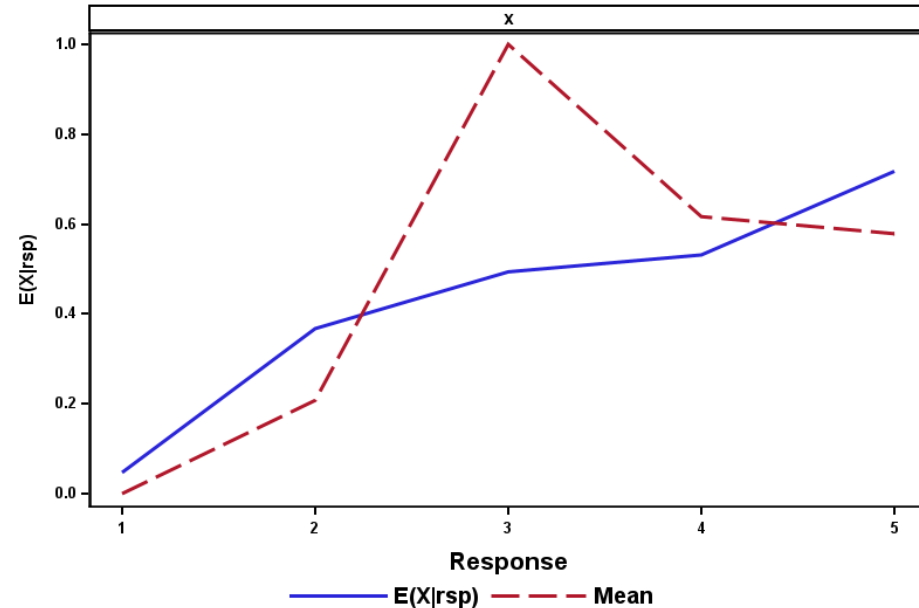
Score Test for the Proportional Odds Assumption

Chi-Square	DF	Pr > ChiSq
24.53	3	<.0001

Empirical Cumulative Logit Plots



Ratio of mean of X within each level of Y, to the expected value of $X|Y=j$



Ordinal Logistic Regression: Adjacent Logits

	a Very Good	b Good	c Moderate	d Poor
a Treatment	p11	p12	p13	p14
b Control	p21	p22	p23	p24

Adjacent logit

- compare probabilities from adjacent cells

Both models produce one odds ratio for the entire table

T: $\text{odds}_T = \frac{A}{B}$

C: $\text{odds}_C = \frac{C}{D}$

The computed odds ratio derived from three ratios:

T: $\text{odds}_{11} = \frac{p_{11}}{p_{12}}$

C: $\text{odds}_{21} = \frac{p_{21}}{p_{22}}$

$= \text{odds}_{11} / \text{odds}_{21}$

OR $= \text{odds}_{12} / \text{odds}_{22}$

$= \text{odds}_{13} / \text{odds}_{23}$

T: $\text{odds}_{12} = \frac{p_{12}}{p_{13}}$

C: $\text{odds}_{22} = \frac{p_{22}}{p_{23}}$

T: $\text{odds}_{13} = \frac{p_{13}}{p_{14}}$

C: $\text{odds}_{23} = \frac{p_{23}}{p_{24}}$



Ordinal Logistic Regression

Adjacent Logits

```
PROC LOGISTIC DATA=indat;  
CLASS x1 / param=ref;  
MODEL y = x1 x2 / link = alogit ;  
SCORE data=scr out=prd;  
RUN;
```



Adacent logit

With $k=4$, have three linear predictors

$$\eta_1 = \text{LOG}(P(y=1)/P(y=2)) = \text{LOG}(p_1/p_2)$$

$$\eta_2 = \text{LOG}(P(y=2)/P(y=3)) = \text{LOG}(p_2/p_3)$$

$$\eta_3 = \text{LOG}(P(y=3)/P(y=4)) = \text{LOG}(p_3/p_4)$$

Solve equations for p_1, p_2, p_3, p_4 in terms of η_1, η_2, η_3

$$p_1 = 1 / \text{total};$$

$$p_2 = \exp(\eta_1) * p_1;$$

$$p_3 = \exp(\eta_2) * p_2;$$

$$p_4 = \exp(\eta_3) * p_3;$$

where

$$\begin{aligned} \text{total} = & 1 + \exp(\eta_1) \\ & + \exp(\eta_1 + \eta_2) \\ & + \exp(\eta_1 + \eta_2 + \eta_3); \end{aligned}$$



Computations of Ordinal Logistic Regression Models in PROC NLMIXED

SAS Global Forum, 2013

Paper 445-2013

Models for Ordinal Response Data

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University of Nebraska Medical Center



Ordinal Logistic Regression

Display results: Effect plots

```
PROC LOGISTIC DATA=indat;  
CLASS x1 x2 / param=ref ;  
MODEL response = x1 x2 / link=clogit aggregate;
```

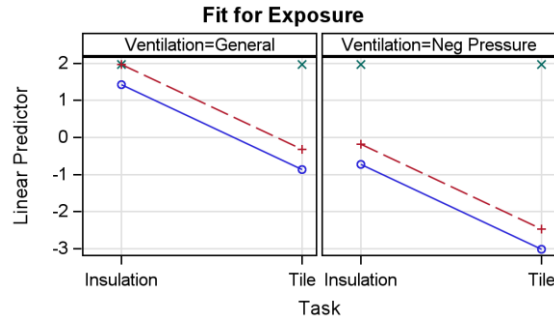
```
EFFECTPLOT interaction(x=x1 plotby=x2 sliceby=response) / link;  
EFFECTPLOT interaction(x=x1 plotby=x2 sliceby=response) / cluster;  
EFFECTPLOT interaction(x=x1 plotby=x2 sliceby=response) / polybar;  
EFFECTPLOT interaction(x=x1 plotby=x2 sliceby=response) / individual;  
EFFECTPLOT interaction(x=x1 plotby=x2 sliceby=response) / individual Noconnect;
```

```
Run;
```

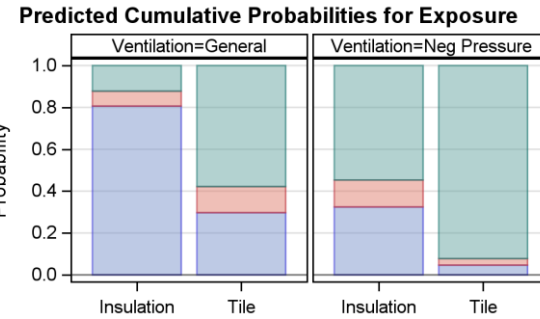
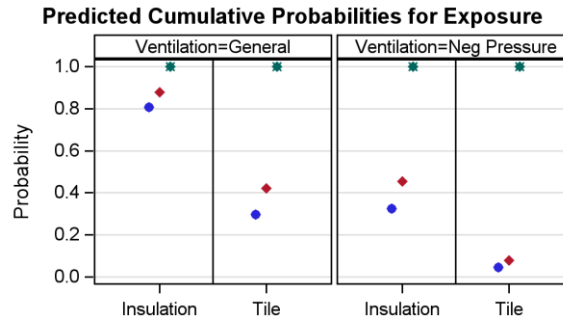


A Few Examples of Effect Plots

LINK

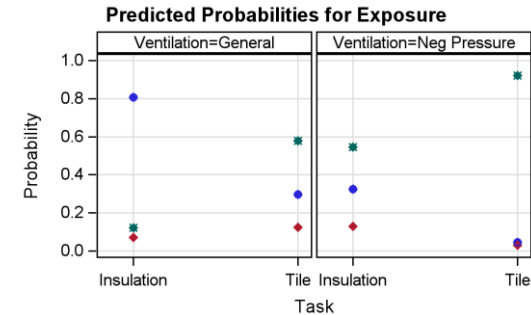
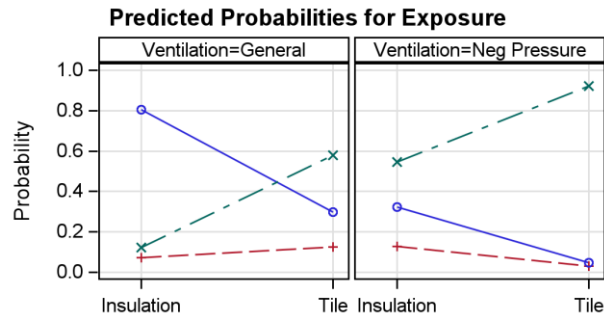


CLUSTER
Cumulative
Probabilities



POLYBAR

Individual
Probabilities



INDIVIDUAL
NOCONNECT



Example 48.4: PROC GENMOD Ice Cream Testing

Counts

	Very Good	Good	Middle	Bad	Very Bad
Brand 1	70	71	151	30	46
Brand 2	20	36	130	74	70
Brand 3	50	55	140	52	50

Row
Percents

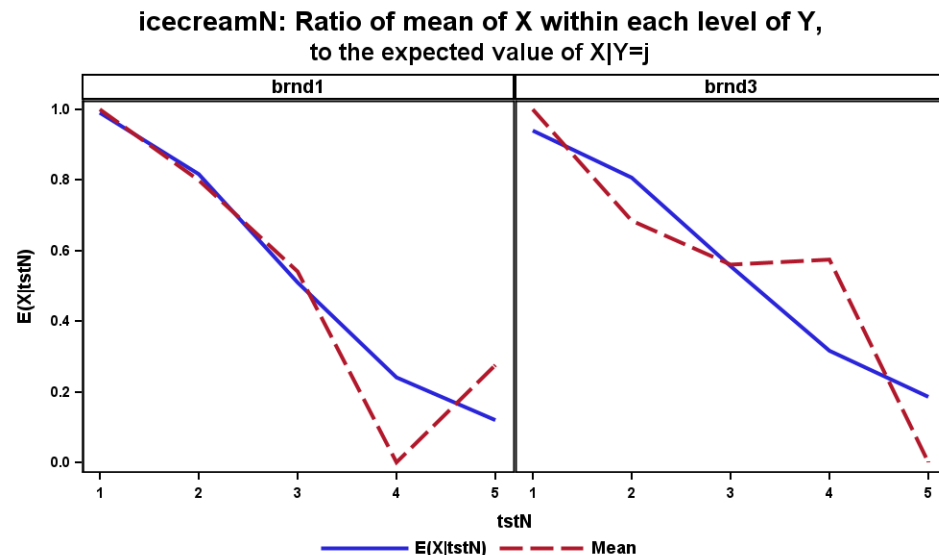
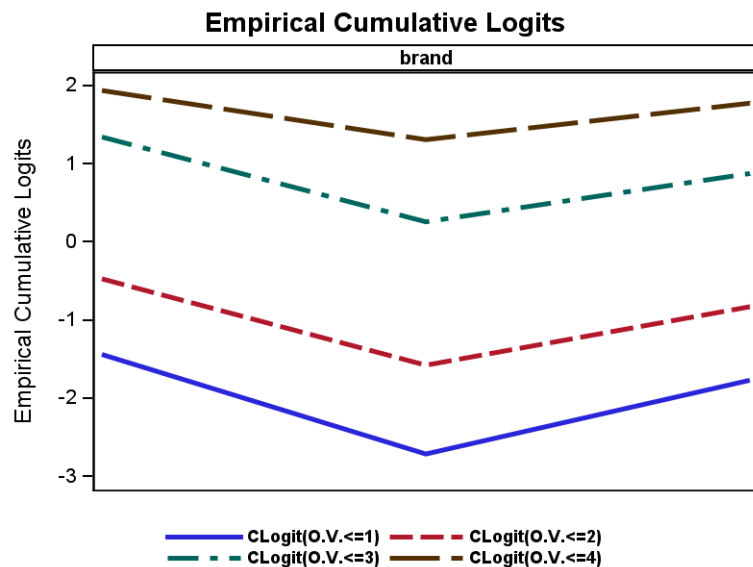
	Very Good	Good	Middle	Bad	Very Bad
Brand 1	19.0	19.3	41.0	8.2	12.5
Brand 2	6.1	10.9	39.4	22.4	21.2
Brand 3	14.4	15.9	40.3	15.0	14.4



Checking the proportional odds assumption

Score Test for the Proportional Odds Assumption

Chi-Square	DF	Pr > ChiSq
11.1216	6	0.0847



LRT: Model 2 (unequal slopes) vs Model 1 (equal slopes)

DF	ChiSq	P
6	9.865	0.13

pvalue prefers equal slopes



Collecting Predicted Values

SCORE statement

```
DATA iceScr;  
brand = 'ice1'; output;  
brand = 'ice2'; output;  
brand = 'ice3'; output;  
run;  
  
PROC LOGISTIC DATA=icecream ;  
FREQ count;  
CLASS brand / param=ref;  
MODEL tstN = brand / link=logit aggregate ;  
SCORE data=iceScr out=prdA;  
TITLE 'LOGISTIC: Adjacent Logit';  
run;  
  
PROC PRINT DATA=prdA; RUN;
```

brand	P_1	P_2	P_3	P_4	P_5
ice1	0.18744	0.18692	0.40526	0.12082	0.09956
ice2	0.07057	0.11233	0.38876	0.18500	0.24333
ice3	0.13756	0.16180	0.41375	0.14549	0.14140



Ice Cream Testing

Predicted Cell Probabilities

Cumulative
logits

	Very Good	Good	Middle	Bad	Very Bad
Brand 1	0.186	0.196	0.405	0.112	0.100
Brand 2	0.076	0.105	0.388	0.193	0.238
Brand 3	0.135	0.161	0.419	0.143	0.141

Odds Ratios

1 vs 3: 1.47
2 vs 3: 0.52

Adjacent
logits

	Very Good	Good	Middle	Bad	Very Bad
Brand 1	0.187	0.187	0.405	0.121	0.100
Brand 2	0.071	0.112	0.389	0.185	0.243
Brand 3	0.138	0.162	0.414	0.145	0.141

Odds Ratios

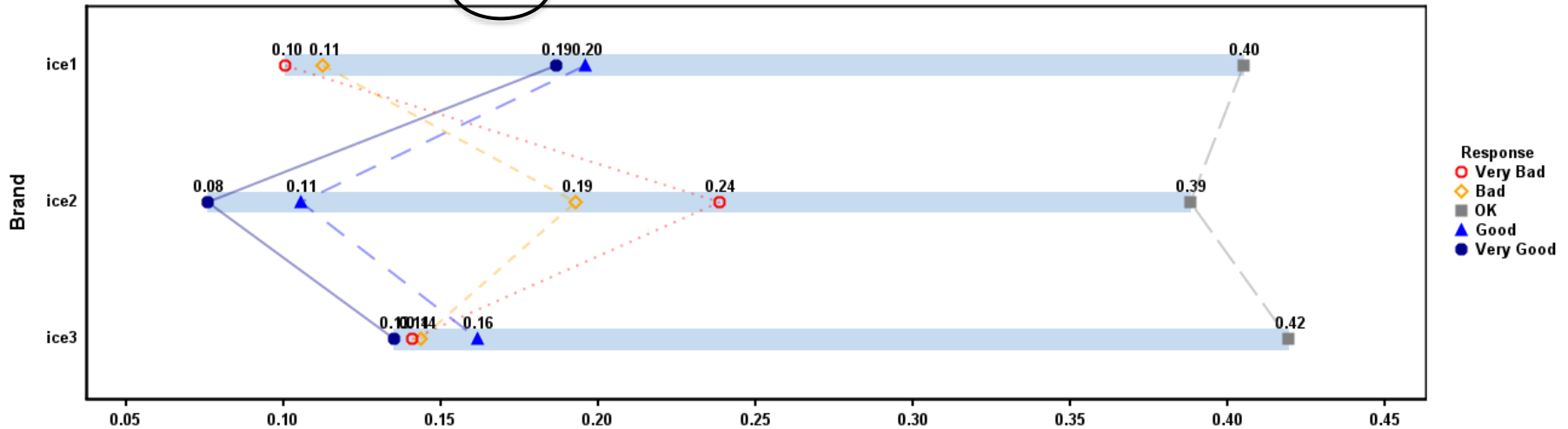
1 vs 3: 1.18
2 vs 3: 0.74

Cell probabilities very close for all three brands and five responses

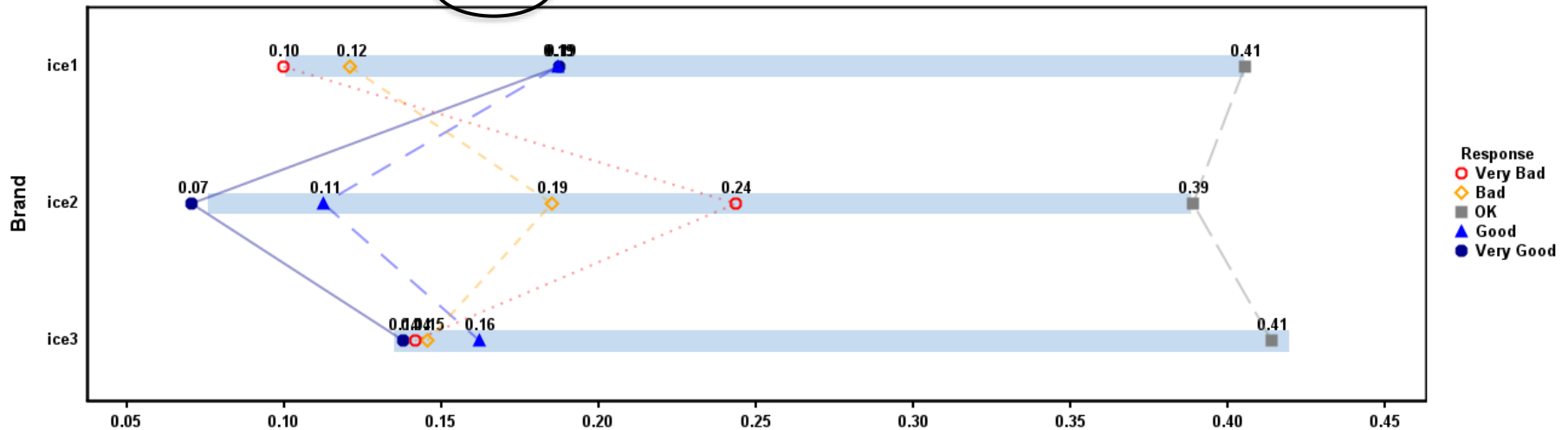


Visual Comparison of Probabilities

Logit: Response Probabilities based on ice cream brand



Alogit: Response Probabilities based on ice cream brand



Cumulative Logits: Ice Cream Testing

Odds Ratios from Predicted Cell Probabilities

Based on
cumulative
logits

	Very Good	Good	Middle	Bad	Very Bad
Brand 1	0.186	0.196	0.405	0.112	0.100
Brand 2	0.076	0.105	0.388	0.193	0.238
Brand 3	0.135	0.161	0.419	0.143	0.141

Odds Ratio

1 vs 3: 1.47

Verify odds ratios from rows 1 and 3:

$$\text{OR 1 vs 3} = \frac{0.186 / (0.196 + 0.405 + 0.112 + 0.100)}{0.135 / (0.161 + 0.419 + 0.143 + 0.141)} = 1.47$$

$$\text{OR 1 vs 3} = \frac{(0.186 + 0.196) / (0.405 + 0.112 + 0.100)}{(0.135 + 0.161) / (0.419 + 0.143 + 0.141)} = 1.47$$

Odds Ratio=0.52 to compare Brand 2 with Brand 3 derived from probabilities in rows 2 and 3



Adjacent Logits: Ice Cream Testing

Odds Ratios from Predicted Cell Probabilities

Based on
adjacent
logits

	Very Good	Good	Middle	Bad	Very Bad
Brand 1	0.187	0.187	0.405	0.121	0.100
Brand 2	0.071	0.112	0.389	0.185	0.243
Brand 3	0.138	0.162	0.414	0.145	0.141

Odds Ratios

1 vs 3: 1.18

Verify Odds Ratios with probabilities from rows 1 and 3

$$\text{OR 1 vs 3} = \frac{0.187 / 0.187}{0.138 / 0.162} = 1.18$$

$$\text{OR 1 vs 3} = \frac{0.187 / 0.405}{0.162 / 0.414} = 1.18$$

Odds Ratio=0.74 to compare Brand 2 to Brand 3 derived in the same manner with rows 2 and 3



Ordinal Logistic Regression

Which model to apply?

Both approaches fit well in similar situations and provide similar substantive results (with large cell counts)

Cumulative logit extends inference to underlying continuum (all k levels)

Adjacent logit gives effects in terms of the categories preferable to interpret categories next to each other rather than the entire continuum



Logistic Regression

Partial Proportional Odds

When diagnostics indicate non-proportional outcomes, apply the "unequalslopes" option in PROC LOGISTIC

```
PROC LOGISTIC DATA=indat;  
CLASS x1 / param=ref;  
MODEL y = x1 x2 / link=clogit unequalslopes;  
RUN;
```

Or specify the specific variable name(s) to apply unequalslopes

```
MODEL y = x1 x2 / link=clogit unequalslopes=x1;
```



Ordinal Logistic Regression with NLMIXED

Odds Ratios for both Cumulative Logits

Proportional Odds: one odds ratio

```
proc nlmixed data=indat(rename=(outcome = y));
parms Int1 -2 Int2 0 Int3 1.5 bx .07 ;

eta1 = Int1 + bx * (trt=1) ; * trt=0 ref category;
eta2 = Int2 + bx * (trt=1) ;
eta3 = Int3 + bx * (trt=1) ;

cp1= 1 / (1 + exp(-eta1));
cp2= 1 / (1 + exp(-eta2));
cp3= 1 / (1 + exp(-eta3));

p1 = cp1;          * calculate single cell probs ;
p2 = cp2 - cp1;    * from the cumulative probs;
p3 = cp3 - cp2;
p4 = 1 - cp3;

lk = (p1**(y EQ 1)) * (p2**(y EQ 2))
      * (p3**(y EQ 3)) * (p4**(y EQ 4)); * ascending;

lk = max(min(lk,1-1E-9),1E-9);
lglik = log(lk);

ESTIMATE 'Odds Ratio' EXP(bx);

MODEL y ~ general(lglik);
TITLE "NLMIXED: ordinal Logr Regr with link = clogit";
run;
```

Partial Proportional odds: three odds ratios

```
parms Int1 -2 Int2 0 Int3 1.5 bx .07 da .1 db .1 ;

eta1 = Int1 + (bx ) * (trt=1) ;
eta2 = Int2 + (bx+da) * (trt=1) ;
eta3 = Int3 + (bx+db) * (trt=1) ;

ESTIMATE 'Odds Ratio 1 vs 234' EXP(bx ) ;
ESTIMATE 'Odds Ratio 12 vs 34' EXP(bx + da) ;
ESTIMATE 'Odds Ratio 123 vs 4' EXP(bx + db) ;
```



Example

Backache Severity Data

Problem Solving: A Statistician's Guide
by Chris Chatfield (1995)

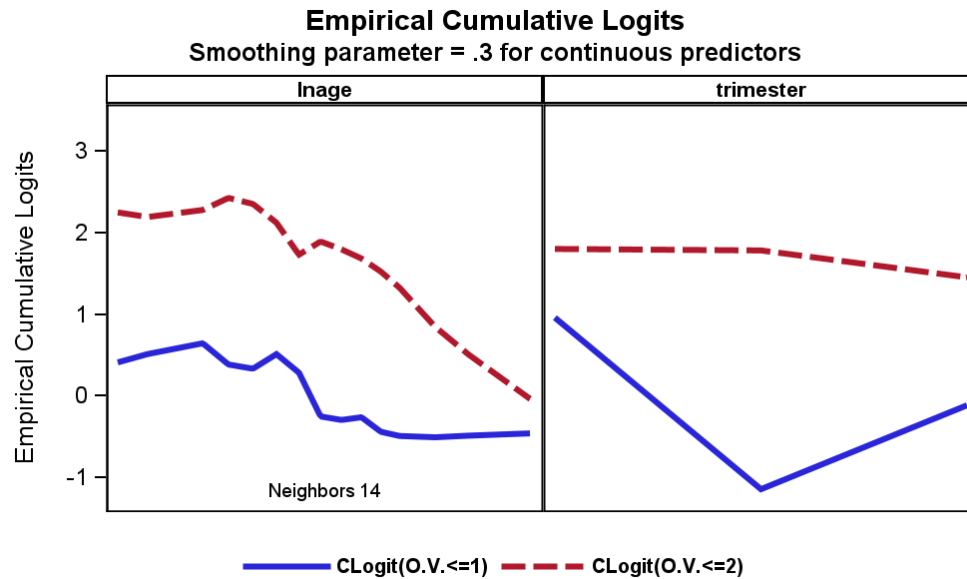
data available in a downloadable text file at:

<https://lib.stat.cmu.edu/datasets>

Evaluate: women who gave birth in a London hospital, is severity of back pain (three ordinal levels) related to trimester pain began (discrete) and age (continuous in years)



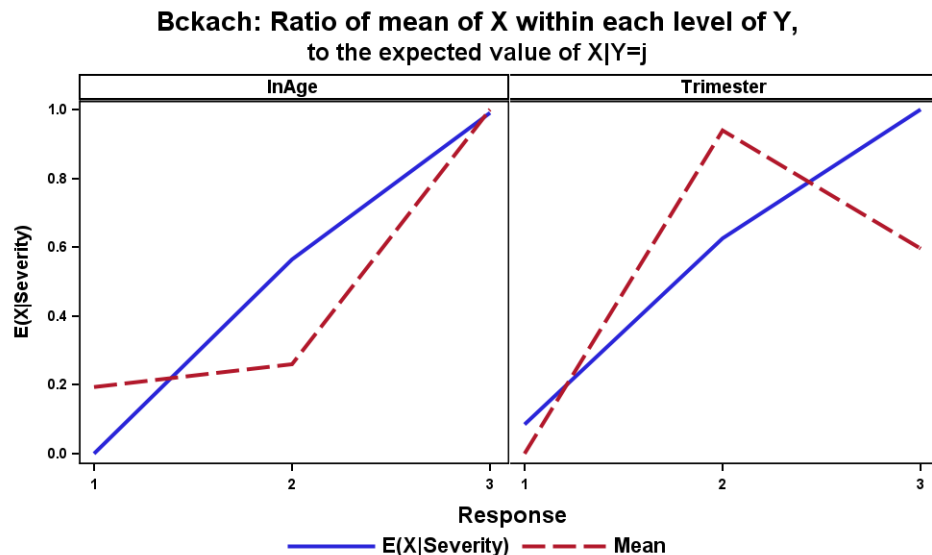
Evaluate Proportional Odds



Score Test

Chi-Square	DF	Pr > ChiSq
22.28	3	<.0001

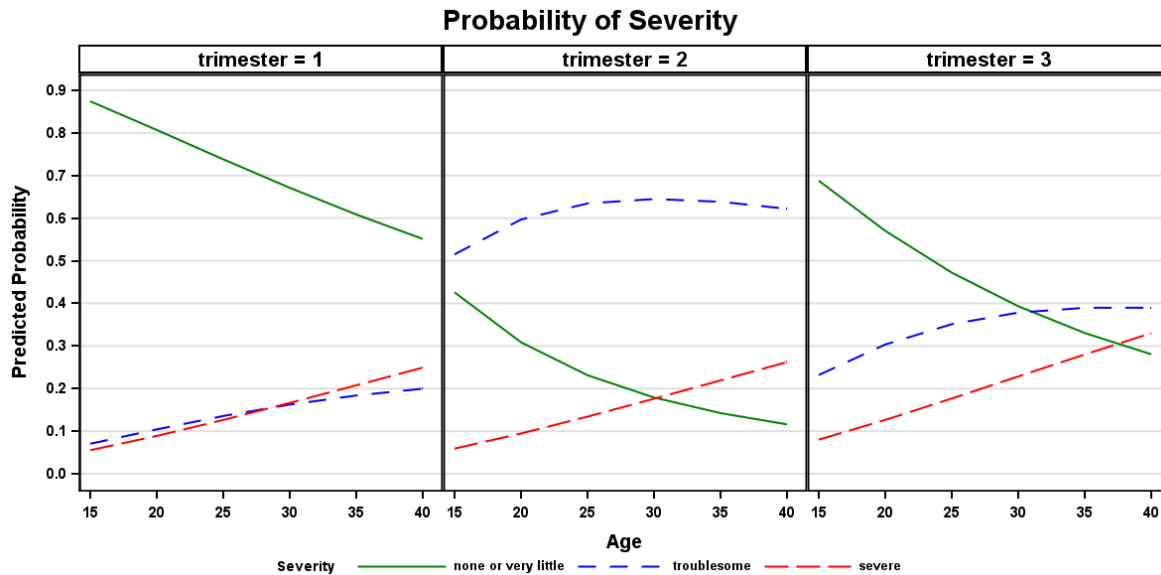
Trimester (panel on right in both plots) shows signs of non-proportional odds



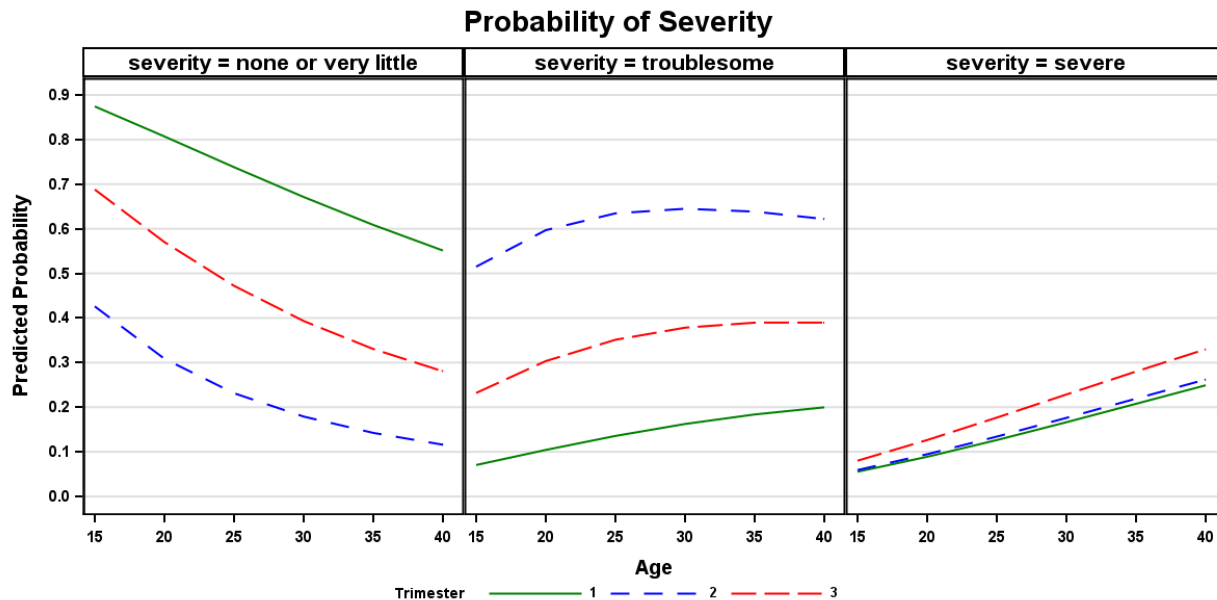
```
proc logistic
    data=Bckach descending;
    class Trimester / param=ref;
    model Severity =lnAge Trimester
    / unequalslopes=Trimester;
Run;
```



Graph Predicted Probabilities



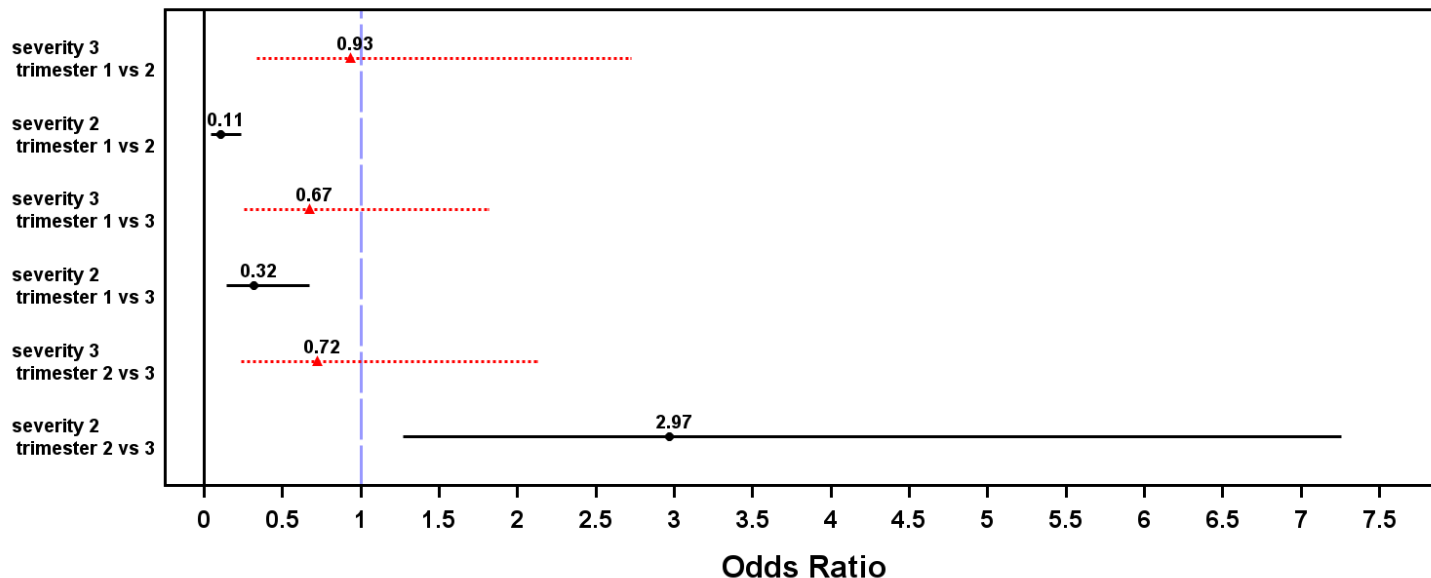
For any of the three trimesters at a specific age, the three probabilities for level of severity sum to 1



Odds Ratios: Descending option

Effect	Odds Ratio	Lower CL	Upper CL
Sev 3: Tri 1 vs 2	0.93	0.34	2.73
Sev 2: Tri 1 vs 2	0.11	0.045	0.24
Sev 3: Tri 1 vs 3	0.67	0.25	1.82
Sev 2: Tri 1 vs 3	0.32	0.15	0.67
Sev 3: Tri 2 vs 3	0.72	0.24	2.13
Sev 2: Tri 2 vs 3	2.97	1.27	7.26

Odds Ratios with Profile Likelihood 95% Confidence Limits



Compute Odds Ratios from Probabilities

descending

Age = 20	Severity		
Trimester	1=none/very little	2=troublesome	3=severe
1	0.80691	0.10425	0.08884
2	0.30863	0.59682	0.09455
3	0.57017	0.30342	0.12641

Severity 3: trimester 1 vs 2

$$\text{OR} = \frac{0.08884 / (0.80691 + 0.10425)}{0.09455 / (0.30863 + 0.59682)} = 0.93$$

Severity 2: trimester 1 vs 2

$$\text{OR} = \frac{(0.08884 + 0.10425) / 0.80691}{(0.09455 + 0.59682) / 0.30863} = 0.11$$

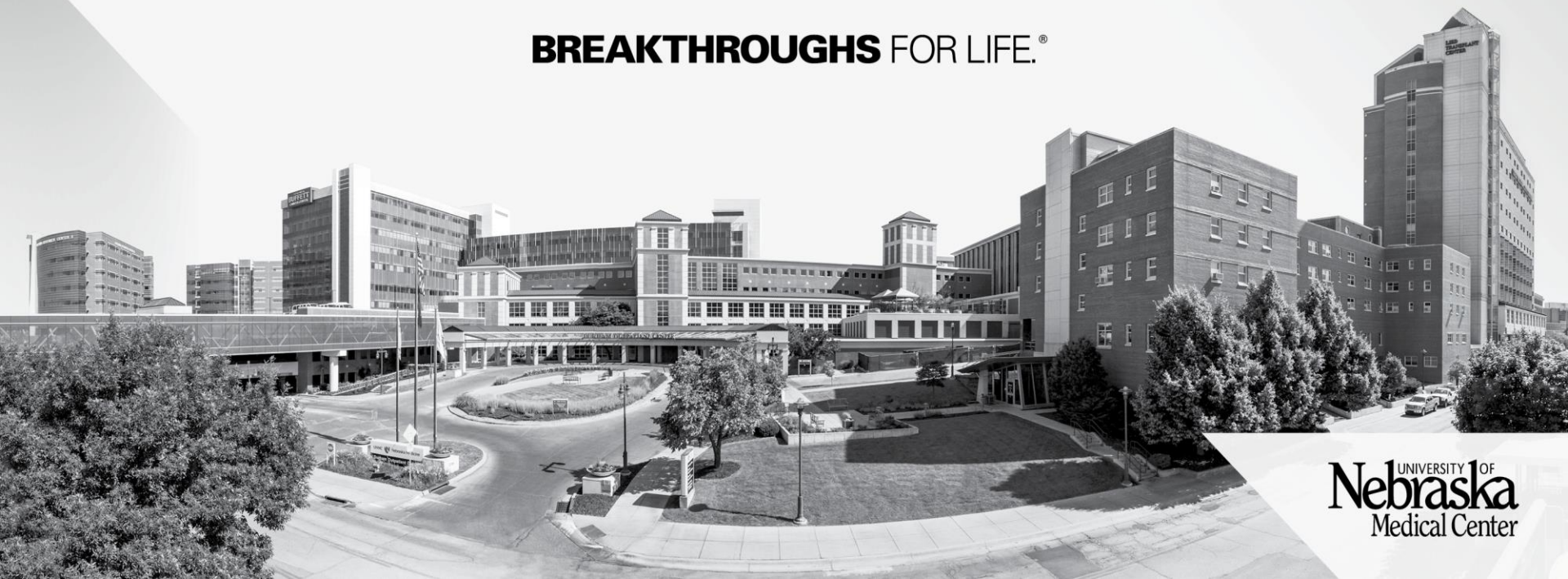
Remaining odds ratios computed in like manner
from rows 1 and 3 (Trimesters 1 and 3)
rows 2 and 3 (Trimesters 2 and 3)





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