Categorical Data Analysis Using SAS and Stata

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May 23, 2016

Outline

- Why do we need to learn categorical data analyses?
- A summary of different categorical data analyses
  - Analyses of contingency tables
  - Regression models
    - Logistic regression
    - Ordered logistic regression
    - Multinomial logistic regression
- Stata commands
- SAS commands
- Interpreting the results
- Predicted probability
- Conclusions

Why Do We Need to Learn Categorical Data Analysis?

- Four measurement levels
  - Nominal (e.g., gender, race)
  - Ordinal (e.g., attitude toward cohabitation)
  - Interval (e.g., temperature)
  - Ratio (e.g., income)
- Categorical variables are those measured at nominal and ordinal levels.
- Interval or ratio variables can be transformed into nominal or ordinal variables, but not the other way around.

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What Is Special about Categorical Variable?

- The distribution of a categorical variable is described by its frequency and proportion rather than by its mean and variance.
- Statistical methods (i.e., t-test, correlation, OLS regression) designed for continuous dependent variables are not adequate for analyzing categorical dependent variables.
- The decision on how to analyze categorical variables is often based on:
  - The measurement level and number of categories in dependent variables
  - The measurement level and number of categories in independent variables
  - Sample size
  - Number of independent variables

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Different Models for Categorical Dependent Variables

Categorical models address three types of questions:

- Examination of contingency tables
  - Proportions
  - Relative risks
  - Odds ratio
- How the characteristics of individuals affect the choice
  - Binary logistic regression
  - Ordered logistic regression
  - Multinomial logistic regression

Analyzing a Two-way Contingency Table

- Analyzing a 2x2 table

Table. Gender and Employment

	Employed	Unemployed
Male	200	200
Female	200	400

Table. Gender and Employment

	Employed	Unemployed
Male	ρ_1	$1-\rho_1$
Female	ρ_2	$1-\rho_2$

$$\text{Difference of Two Proportions} = \pi_1 - \pi_2 \approx \rho_1 - \rho_2$$

$$SE = \sqrt{\frac{\rho_1(1-\rho_1)}{n_1} + \frac{\rho_2(1-\rho_2)}{n_2}}$$

Analyzing a Two-way Contingency Table (Cont.)

$$\text{Relative Risk} = \frac{\pi_1}{\pi_2}$$

Odds Ratio

$$\text{Odds Ratio} = \frac{\text{Odds1}}{\text{Odds2}}$$

$$= \frac{\pi 1 / (1-\pi 1)}{\pi 2 / (1-\pi 2)} = \frac{\pi 11 / \lambda 12}{\pi 21 / \pi 22} = \frac{\pi 11 \cdot \pi 22}{\pi 12 \cdot \pi 21}$$

$$SE = \sqrt{\frac{1}{n11} + \frac{1}{n12} + \frac{1}{n21} + \frac{1}{n22}}$$

Example

- Data

  P1 = 200/400 = 0.5

  P2 = 200/600 = 0.33

  – Difference of two proportions

    P1 - P2 = 0.17

  – Relative risk

    P1/P2 = 1.51

  – Odds Ratio

    (200*400)/(200*200) = 2

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Analyzing a Three-way Contingency Table

- A three-way contingency table can be viewed as multiple two-way contingency tables created at different levels of a third variable.

- Example:

Table. Relations among Country, Gender, and Employment

	County A		Country B	
	Employed	Unemploye	Employed	Unemployed
Male	180	120	20	80
Female	120	80	80	320

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Example

– Difference of proportion

Country A: (180/300) – (120/200)=0

Country B: (20/100) –(80/320)=0

– Relative risk

Country A: (180/300)/(120/200)=0.6/0.6=1

Country B: (20/100) –(80/320)=0.2/0.2=1

– Odds Ratio

Country A: (180*80)/(120*120)=1

Country B: (20*320)*(80*80)=1

Models for Examining How Characteristics of Individuals Affect Choices

Logistic Regression

$$\log\left(\frac{p_1}{p_2}\right) = \log\left(\frac{p_1}{1-p_1}\right) = \alpha + \beta\chi$$

$$\pi(\chi) = \frac{\exp(\alpha + \beta\chi)}{1 + \exp(\alpha + \beta\chi)} = \frac{e^{\alpha+\beta\chi}}{1 + e^{\alpha+\beta\chi}}$$

Ordered Logistic Regression

$$p(Y \le j) = \pi_1 + \ldots + \pi_{j,}\ j = 1, \ldots, J$$

$$\operatorname{logit}[p(Y \le j)] = \log\left[\frac{p(Y \le j)}{1 - p(Y \le j)}\right] = \log\left[\frac{\pi_1 + \ldots + \pi_{j,}}{\pi_{j+1} + \ldots + \pi_{J,}}\right],\ j = 1, \ldots, J$$

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Models for Examining How Characteristics of Individuals Affect Choices (Cont.)

Multinomial Logistic Regression

$$\log(\frac{p_j}{p_J}) = \alpha_j + \beta_j \chi,\ j = 1, \ldots, J-1$$

$$\log(\frac{p_a}{p_b}) = \log(\frac{\frac{p_a}{p_J}}{\frac{p_b}{p_J}}) = \log(\frac{p_a}{p_J}) - \log(\frac{p_b}{p_J})$$

$$= (\alpha_{\mathrm{a}} + \beta_a \chi) - (\alpha_{\mathrm{b}} + \beta_b \chi)$$

$$= (\alpha_\alpha - \alpha_b) + (\beta_a - \beta_b)\chi$$

Relations among These Three Models

- Ordered logistic regression and multinomial logistic regression are an extension of logistic regression.

- Both ordered and multinomial logistic regression can be treated as models simultaneously estimating a series of logistic regression.

- Ordered logistic regression assumes different intercepts, but the same slope for different categories, while multinomial logistic regression assumes different intercept and slope parameters for different categories.

A List of Variables in the Data

variable name	variable label	Label Value	Label Label
aid	ID	57101310 - 99719978	
married	Marital Status	0	Not married
		1	Married
educ	Education	1	Less than High School
		2	High School
		3	Some college
		4	colleges or more
union	Union Status	0	single
		1	cohabiting
		2	married
female	Female	0	Male
		1	Female
age	Age		24-33
agesq	Age squared		576-1089
femaleage	Interaction term of female and age		0-33

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Data for Logistic Regression, Ordered Logistic Regression, and Multinomial Logistic Regression

	aid	married	educ	union	female	age	agesq	femaleage
1	57101310	1	2	2	1	31	961	31
2	57103869	0	1	0	0	32	1024	0
3	57109625	0	1	0	0	27	729	0
4	57111071	0	3	0	0	27	729	0
5	57113943	0	3	1	0	29	841	0
6	57117542	0	1	0	0	28	784	0
7	57118381	1	3	2	1	25	625	25
8	57118943	1	4	2	1	29	841	29
9	57120005	0	4	0	0	26	676	0
10	57120046	1	3	2	0	31	961	0
11	57120371	1	2	2	1	31	961	31
12	57121404	1	4	2	1	28	784	28
13	57121476	0	2	0	1	27	729	27
14	57127241	0	3	1	1	26	676	26
15	57129567	0	3	1	0	27	729	0
16	57131432	1	3	2	0	29	841	0
17	57131909	0	3	1	0	26	676	0
18	57133772	0	3	0	1	26	676	26
19	57134457	0	3	0	1	28	784	28
20	57134967	0	1	1	1	26	676	26

Stata Commands

Logistic Regression

```
logit married female age femaleage
logit married female age femaleage, or
```

Ordered Logistic Regression

```
ologit educ female age femaleage
ologit educ female age femaleage, or
```

Multinomial Logistic Regression

```
mlogit union female age femaleage,
base(0)
```

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SAS Commands

Logistic Regression

```
Proc Logistic data = in.annotated_3_2;
Format married marriedf. educ educf.;
Model married = educ female age femaleage;
run;
```

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SAS Commands

Ordered Logistic Regression

```
Proc Logistic data = in.annotated descending;
Format educ educf. female femalef.;
Model educ = female age femaleage;
run;

PROC QLIM data = in.annotated;
MODEL educ = female age
femaleage/DISCRETE (DIST=LOGISTIC);
RUN;
```

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SAS and Stata Commands

Multinomial Logistic Regression

```
proc logistic data = in.annotated_3_2;
class union (ref = "0");
model union = female age femaleage/ link = glogit;
run;
```

Interpreting the Results

- The sample size
- The reference category
- The regression coefficients
- The odds ratio

Predicted Probability

- Predicted probability is useful to describe the results
- Odds = Exp(the sum of coefficients)
- Predicted Probability = Odds/(1+Odds)
- You can present predicted probability with graphs

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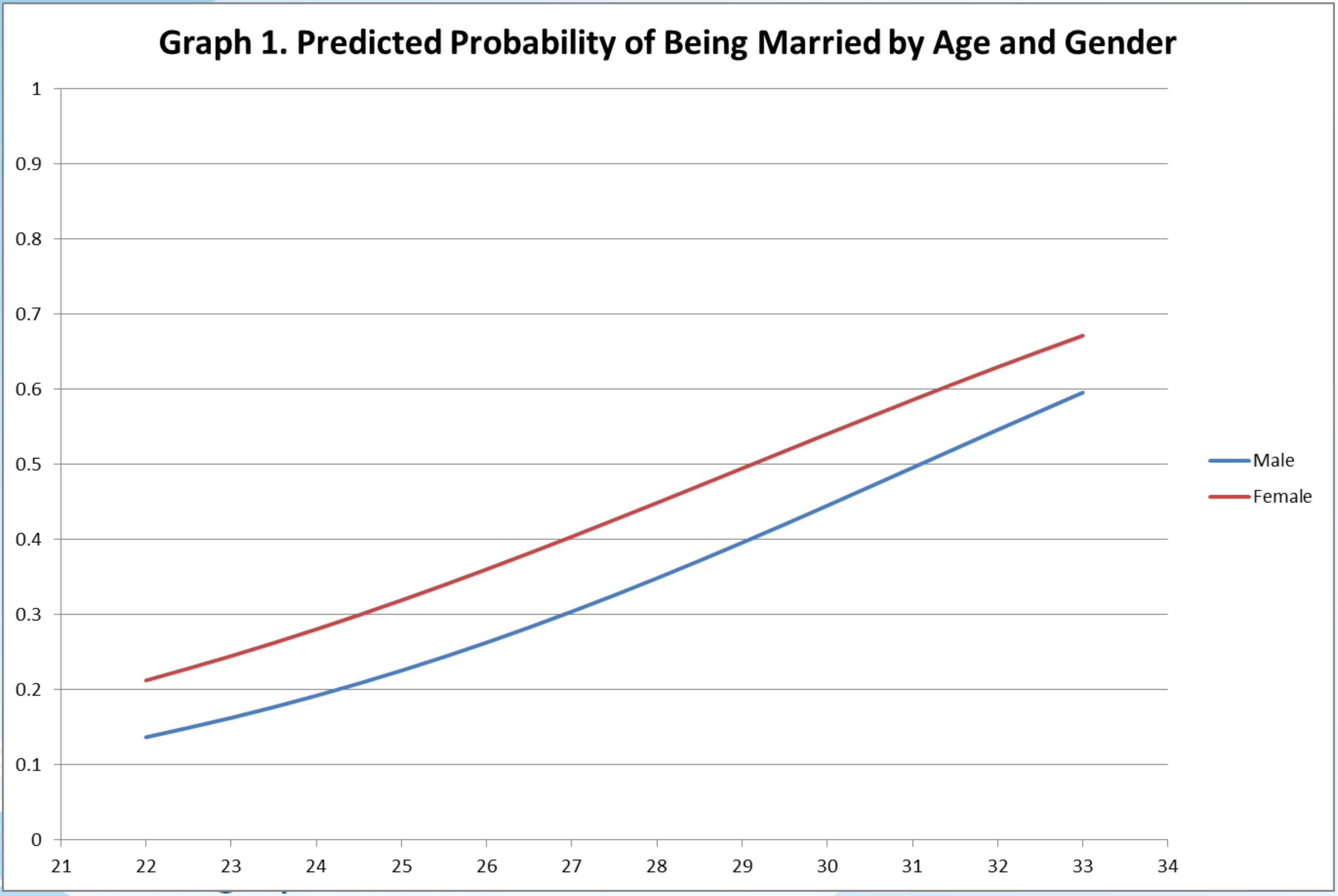
Predicted Probability (continued)

Table 3. Predicated Probability for Male and Female Respondents

Intercept	Female		Age		Age*Female		Sum of coefficents	Odds Ratio	Predicted Probability
coefficent	value	coefficent	value	coefficent	value	coefficent			
-6.295917	0	0.9380865	22	0.2025471	0	-0.0185092	-1.8398808	0.158836358	0.137065391
-6.295917	0	0.9380865	23	0.2025471	0	-0.0185092	-1.6373337	0.194497941	0.162828193
-6.295917	0	0.9380865	24	0.2025471	0	-0.0185092	-1.4347866	0.238166183	0.192353972
-6.295917	0	0.9380865	25	0.2025471	0	-0.0185092	-1.2322395	0.291638721	0.225789701
-6.295917	0	0.9380865	26	0.2025471	0	-0.0185092	-1.0296924	0.357116793	0.263143743
-6.295917	0	0.9380865	27	0.2025471	0	-0.0185092	-0.8271453	0.437295855	0.30424902
-6.295917	0	0.9380865	28	0.2025471	0	-0.0185092	-0.6245982	0.53547654	0.348736386
-6.295917	0	0.9380865	29	0.2025471	0	-0.0185092	-0.4220511	0.655700532	0.396026044
-6.295917	0	0.9380865	30	0.2025471	0	-0.0185092	-0.219504	0.802916946	0.44534328
-6.295917	0	0.9380865	31	0.2025471	0	-0.0185092	-0.0169569	0.983186059	0.495760877
-6.295917	0	0.9380865	32	0.2025471	0	-0.0185092	0.1855902	1.203928789	0.546264832
-6.295917	0	0.9380865	33	0.2025471	0	-0.0185092	0.3881373	1.474232182	0.595834212
-6.295917	1	0.9380865	22	0.2025471	22	-0.0185092	-1.3089967	0.270090903	0.212654781
-6.295917	1	0.9380865	23	0.2025471	23	-0.0185092	-1.1249588	0.324665843	0.245092636
-6.295917	1	0.9380865	24	0.2025471	24	-0.0185092	-0.9409209	0.390268272	0.280714363
-6.295917	1	0.9380865	25	0.2025471	25	-0.0185092	-0.756883	0.469126417	0.319323383
-6.295917	1	0.9380865	26	0.2025471	26	-0.0185092	-0.5728451	0.563918749	0.360580592
-6.295917	1	0.9380865	27	0.2025471	27	-0.0185092	-0.3888072	0.67786495	0.404004476
-6.295917	1	0.9380865	28	0.2025471	28	-0.0185092	-0.2047693	0.814835277	0.448985805
-6.295917	1	0.9380865	29	0.2025471	29	-0.0185092	-0.0207314	0.979482018	0.494817336
-6.295917	1	0.9380865	30	0.2025471	30	-0.0185092	0.1633065	1.177397507	0.540736133
-6.295917	1	0.9380865	31	0.2025471	31	-0.0185092	0.3473444	1.415304072	0.585973455
-6.295917	1	0.9380865	32	0.2025471	32	-0.0185092	0.5313823	1.701282367	0.629805454
-6.295917	1	0.9380865	33	0.2025471	33	-0.0185092	0.7154202	2.04504583	0.671597718

Predicted Probability (continued)



Conclusions

- If you have categorical dependent variables, you need to choose adequate methods to analyze them.
- You need to choose the regression models that fit your data and research questions.
- If you have event counts (e.g., the number of accidents), you need to use other models such as Poisson regression, Log-linear model, or Negative binomial regression for analyses.
- For additional help with categorical data analysis, feel free to contact me at wuh@bgsu.edu and 372-3119.

```
*************************
* Logistic Regression
*************************

. logit married female age femaleage

Iteration 0:   log likelihood = -3486.5653
Iteration 1:   log likelihood = -3394.8573
Iteration 2:   log likelihood = -3394.6262
Iteration 3:   log likelihood = -3394.6262

Logistic regression                               Number of obs   =       5114
                                                  LR chi2(3)      =     183.88
                                                  Prob > chi2     =     0.0000
Log likelihood = -3394.6262                       Pseudo R2       =     0.0264

------------------------------------------------------------------------------
     married |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |   .9380865    .934408     1.00   0.315    -.8933196    2.769493
         age |   .2025471   .0242963     8.34   0.000     .1549273    .2501669
   femaleage |  -.0185092   .0326631    -0.57   0.571    -.0825278    .0455093
       _cons |  -6.295917   .6988726    -9.01   0.000    -7.665682   -4.926152
------------------------------------------------------------------------------

.
. logit married female age femaleage,or

Iteration 0:   log likelihood = -3486.5653
Iteration 1:   log likelihood = -3394.8573
Iteration 2:   log likelihood = -3394.6262
Iteration 3:   log likelihood = -3394.6262

Logistic regression                               Number of obs   =       5114
                                                  LR chi2(3)      =     183.88
                                                  Prob > chi2     =     0.0000
Log likelihood = -3394.6262                       Pseudo R2       =     0.0264

------------------------------------------------------------------------------
     married | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |   2.555088   2.387494     1.00   0.315     .4092948    15.95054
         age |   1.224518   .0297512     8.34   0.000     1.167573     1.28424
   femaleage |    .981661   .0320641    -0.57   0.571     .9207858    1.046561
       _cons |   .0018438   .0012886    -9.01   0.000     .0004686    .0072544
------------------------------------------------------------------------------

.
*************************
* Ordered Logistic Regression
*************************
.
. ologit educ female age femaleage

Iteration 0:   log likelihood = -6252.7947
Iteration 1:   log likelihood = -6206.1378
Iteration 2:   log likelihood = -6206.0689
Iteration 3:   log likelihood = -6206.0689

Ordered logistic regression                       Number of obs   =       5113
                                                  LR chi2(3)      =      93.45
                                                  Prob > chi2     =     0.0000
Log likelihood = -6206.0689                       Pseudo R2       =     0.0075

------------------------------------------------------------------------------
        educ |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |   1.877126   .8172138     2.30   0.022      .275416    3.478835
         age |   -.010898   .0208886    -0.52   0.602    -.0518389    .0300429
   femaleage |  -.0494917   .0286535    -1.73   0.084    -.1056516    .0066682
-------------+----------------------------------------------------------------
       /cut1 |   -2.54953   .5995614                     -3.724648   -1.374411
       /cut2 |  -1.213573   .5982002                     -2.386024   -.0411226
       /cut3 |   .6857857   .5979509                     -.4861766    1.857748
```

```
------------------------------------------------------------------------------

.
. ologit educ female age femaleage,or

Iteration 0:   log likelihood = -6252.7947
Iteration 1:   log likelihood = -6206.1378
Iteration 2:   log likelihood = -6206.0689
Iteration 3:   log likelihood = -6206.0689

Ordered logistic regression                       Number of obs   =       5113
                                                  LR chi2(3)      =      93.45
                                                  Prob > chi2     =     0.0000
Log likelihood = -6206.0689                       Pseudo R2       =     0.0075

------------------------------------------------------------------------------
        educ | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |   6.534694   5.340242     2.30   0.022     1.317079    32.42193
         age |   .9891612   .0206622    -0.52   0.602     .9494818    1.030499
   femaleage |   .9517131   .0272699    -1.73   0.084     .8997381     1.00669
-------------+----------------------------------------------------------------
       /cut1 |   -2.54953   .5995614                     -3.724648   -1.374411
       /cut2 |  -1.213573   .5982002                     -2.386024   -.0411226
       /cut3 |   .6857857   .5979509                     -.4861766    1.857748
------------------------------------------------------------------------------

.
.
**********************************
* Multinomial Logistic Regression
***********************************
.
. mlogit union female age femaleage, base(0)

Iteration 0:   log likelihood =  -5376.261
Iteration 1:   log likelihood = -5282.5618
Iteration 2:   log likelihood = -5282.3053
Iteration 3:   log likelihood = -5282.3053

Multinomial logistic regression                   Number of obs   =       5114
                                                  LR chi2(6)      =     187.91
                                                  Prob > chi2     =     0.0000
Log likelihood = -5282.3053                       Pseudo R2       =     0.0175

------------------------------------------------------------------------------
       union |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
single       |  (base outcome)
-------------+----------------------------------------------------------------
cohabiting   |
      female |   .8175782   1.228829     0.67   0.506    -1.590882    3.226038
         age |   .0030635    .030982     0.10   0.921    -.0576601    .0637871
   femaleage |  -.0239002   .0435381    -0.55   0.583    -.1092333    .0614329
       _cons |  -.8159613   .8787378    -0.93   0.353    -2.538256    .9063331
-------------+----------------------------------------------------------------
married      |
      female |    1.22508   1.024113     1.20   0.232    -.7821444    3.232305
         age |   .2035444    .026309     7.74   0.000     .1519797    .2551092
   femaleage |   -.026943   .0358749    -0.75   0.453    -.0972566    .0433705
       _cons |  -5.930568   .7551726    -7.85   0.000    -7.410679   -4.450457
------------------------------------------------------------------------------
```

The SAS System

*** Logistic Regression***

The LOGISTIC Procedure

Model Information		
Data Set	IN.ANNOTATED_3_2	annotated_3_2 dataset written by Stat/Transfer Ver. 11.2.2106.0521
Response Variable	married	Current marital status
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	5114
Number of Observations Used	5114

Response Profile

Ordered Value	married	Total Frequency
1	married	2172
2	not married	2942

Probability modeled is married='married'.

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	6975.131	6797.252
SC	6981.670	6823.411
-2 Log L	6973.131	6789.252

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	183.8783	3	<.0001
Score	180.7636	3	<.0001
Wald	175.3151	3	<.0001

Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	-6.2959	0.6989	81.1563	<.0001
female	1	0.9381	0.9344	1.0079	0.3154
age	1	0.2025	0.0243	69.4981	<.0001
femaleage	1	-0.0185	0.0327	0.3211	0.5709

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Wald Confidence Limits**	
female	2.555	0.409	15.951
age	1.225	1.168	1.284
femaleage	0.982	0.921	1.047

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	56.8	**Somers' D**	0.220
Percent Discordant	34.8	**Gamma**	0.240
Percent Tied	8.4	**Tau-a**	0.107
Pairs	6390024	**c**	0.610

The SAS System

*** Ordered Logistic Regression, Using “Proc Logistic” Procedure ***

The LOGISTIC Procedure

Model Information

Data Set	IN.ANNOTATED_3_2	annotated_3_2 dataset written by Stat/Transfer Ver. 11.2.2106.0521
Response Variable	educ	Education
Number of Response Levels	4	
Model	cumulative logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	5114
Number of Observations Used	5113

Response Profile

Ordered Value	educ	Total Frequency
1	colleges or more	1668
2	Some college	2211
3	Less than High School	399
4	High School	835

Probabilities modeled are cumulated over the lower Ordered Values.

Note: 1 observation was deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Score Test for the Proportional Odds Assumption

Chi-Square	DF	Pr > ChiSq
20.3374	6	0.0024

Model Fit Statistics		
Criterion	**Intercept Only**	**Intercept and Covariates**
AIC	12511.589	12419.182
SC	12531.208	12458.419
-2 Log L	12505.589	12407.182

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	98.4077	3	<.0001
Score	97.9548	3	<.0001
Wald	97.1834	3	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	**colleges or more**	1	-0.5802	0.5974	0.9433	0.3314
Intercept	**Some college**	1	1.3187	0.5977	4.8672	0.0274
Intercept	**Less than High School**	1	1.8133	0.5981	9.1931	0.0024
female		1	2.0949	0.8184	6.5518	0.0105
age		1	-0.0146	0.0209	0.4922	0.4830
femaleage		1	-0.0572	0.0287	3.9675	0.0464

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Wald Confidence Limits**	
female	8.124	1.634	40.405
age	0.985	0.946	1.027
femaleage	0.944	0.893	0.999

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	52.3	**Somers' D**	0.120
Percent Discordant	40.3	**Gamma**	0.130

Association of Predicted Probabilities and Observed Responses			
Percent Tied	7.5	**Tau-a**	0.081
Pairs	8807799	**c**	0.560

The SAS System

*** Ordered Logistic Regression, Using “Proc QLIM” Procedure ***

The QLIM Procedure

Discrete Response Profile of educ		
Index	**Value**	**Total Frequency**
1	1	399
2	2	835
3	3	2211
4	4	1668

Model Fit Summary	
Number of Endogenous Variables	1
Endogenous Variable	educ
Number of Observations	5113
Missing Values	1
Log Likelihood	-6206
Maximum Absolute Gradient	0.0002955
Number of Iterations	18
Optimization Method	Quasi-Newton
AIC	12424
Schwarz Criterion	12463

Goodness-of-Fit Measures		
Measure	**Value**	**Formula**
Likelihood Ratio (R)	93.451	2 * (LogL - LogL0)
Upper Bound of R (U)	12506	- 2 * LogL0
Aldrich-Nelson	0.0179	R / (R+N)
Cragg-Uhler 1	0.0181	1 - exp(-R/N)
Cragg-Uhler 2	0.0198	(1-exp(-R/N)) / (1-exp(-U/N))

Goodness-of-Fit Measures

Measure	Value	Formula
Estrella	0.0182	1 - (1-R/U)^(U/N)
Adjusted Estrella	0.0159	1 - ((LogL-K)/LogL0)^(-2/N*LogL0)
McFadden's LRI	0.0075	R / U
Veall-Zimmermann	0.0253	(R * (U+N)) / (U * (R+N))
McKelvey-Zavoina	0.0596	
N = # of observations, K = # of regressors		

Algorithm converged.

Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	2.549530	0.599559	4.25	<.0001
female	1	1.877126	0.817215	2.30	0.0216
age	1	-0.010898	0.020889	-0.52	0.6019
femaleage	1	-0.049492	0.028654	-1.73	0.0841
_Limit2	1	1.335956	0.045318	29.48	<.0001
_Limit3	1	3.235315	0.055188	58.62	<.0001

The SAS System

*** Multinomial Logistic Regression ***

The LOGISTIC Procedure

Model Information		
Data Set	IN.ANNOTATED_3_2	annotated_3_2 dataset written by Stat/Transfer Ver. 11.2.2106.0521
Response Variable	union	Union Status
Number of Response Levels	3	
Model	generalized logit	
Optimization Technique	Newton-Raphson	

Number of Observations Read	5114
Number of Observations Used	5114

Response Profile

Ordered Value	union	Total Frequency
1	0	1936
2	1	1006
3	2	2172

Logits modeled use union=0 as the reference category.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	10756.522	10580.611
SC	10769.601	10632.929
-2 Log L	10752.522	10564.611

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	187.9113	6	<.0001
Score	185.1487	6	<.0001
Wald	179.5235	6	<.0001

Type 3 Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
female	2	1.4589	0.4822
age	2	69.4399	<.0001
femaleage	2	0.6271	0.7308

Analysis of Maximum Likelihood Estimates						
Parameter	**union**	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	**1**	1	-0.8139	0.8787	0.8579	0.3543
Intercept	**2**	1	-5.9266	0.7551	61.5971	<.0001
female	**1**	1	0.8154	1.2288	0.4403	0.5070
female	**2**	1	1.2211	1.0241	1.4217	0.2331
age	**1**	1	0.00300	0.0310	0.0094	0.9229
age	**2**	1	0.2034	0.0263	59.7839	<.0001
femaleage	**1**	1	-0.0238	0.0435	0.2995	0.5842
femaleage	**2**	1	-0.0268	0.0359	0.5585	0.4549

Odds Ratio Estimates				
Effect	**union**	**Point Estimate**	**95% Wald Confidence Limits**	
female	**1**	2.260	0.203	25.124
female	**2**	3.391	0.456	25.236
age	**1**	1.003	0.944	1.066
age	**2**	1.226	1.164	1.290
femaleage	**1**	0.976	0.897	1.063
femaleage	**2**	0.974	0.907	1.044