



Bernoulli model for NESARC data

Contents

1.	The data.....	1
2.	Exploring the data	2
3.	The model.....	3
4.	Setting up the analysis	4
5.	Discussion of results.....	8
6.	Alternative model.....	13

1. The data

The data set is from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC), which was designed to be a longitudinal survey with its first wave fielded in 2001–2002. This data contains information on the occurrences of major depression, family history of major depression and dysthymia of dysthymia respondents.

	PSU	WEIGHT	AGE	AGE_GM	SEX	FULLTIME	YR2_DEP	WHITEOTH	BLACK
1	1001.00	4270.49	24.00	-22.36	0.00	1.00	0.00	1.00	0.00
2	1001.00	1899.53	33.00	-13.36	0.00	0.00	0.00	1.00	0.00
3	1001.00	2370.19	60.00	13.64	0.00	1.00	0.00	0.00	1.00
4	1001.00	3897.07	29.00	-17.36	1.00	1.00	0.00	1.00	0.00
5	1001.00	6610.44	80.00	33.64	1.00	0.00	0.00	1.00	0.00
6	1001.00	3789.37	36.00	-10.36	1.00	0.00	0.00	0.00	1.00
7	1001.00	3167.29	66.00	19.64	1.00	1.00	0.00	1.00	0.00
8	1001.00	959.70	65.00	18.64	1.00	0.00	0.00	0.00	1.00
9	1001.00	3167.29	71.00	24.64	1.00	0.00	0.00	1.00	0.00
10	1001.00	7231.97	54.00	7.64	1.00	0.00	0.00	1.00	0.00
11	1001.00	3428.06	72.00	25.64	0.00	0.00	0.00	1.00	0.00
12	1001.00	7231.97	53.00	6.64	1.00	0.00	0.00	1.00	0.00
13	1001.00	6982.04	64.00	17.64	1.00	0.00	0.00	1.00	0.00
14	1001.00	7402.76	33.00	-13.36	0.00	1.00	0.00	1.00	0.00
15	1001.00	3428.06	67.00	20.64	0.00	0.00	0.00	1.00	0.00

The variables of interest are:

- PSU denotes the Census 2000/2001 Supplementary Survey (C2SS) primary sampling unit.

4. Setting up the analysis

Open the LISREL spreadsheet **nesarc_ber.lsf** used during the exploratory analysis discussed previously. The next step is to describe the model to be fitted. We use the LISREL interface to provide the model specifications. From the main menu bar, select the **Multilevel, Generalized Linear Model, Title and Options** option.

The multilevel generalized linear model contains five consecutive dialog boxes. The **Titles and Options** dialog box as shown below enables the user to input the title, maximum number of iteration, convergence criterion, missing values, and method and request additional output. Enter a title for the analysis in the **Title** text boxes (optional) and keep all the other settings as default.

Title and Options

Title:
Bernoulli Level-2 model, random intercept and slope

Maximum Number of Iterations: 100

Convergence Criterion: 0.0001

Missing Data Value: -999999

Dependent Missing Value: -999999

Optimization Method

MAP Quadrature

Number of Quadrature Points: 10

Additional Output

Residual files No data summary

Asymptotic covariance

Next >> Cancel OK

To build syntax, proceed to the Random Variables screen and click the Finish button

Proceed to the **ID and Weights** screen by clicking on the **Next** button. Highlight PSU from the **Variables in data** list and click on the upper **Add** button to select it as the **Level-2 ID variable**. Similarly, highlight the variable WEIGHT and click on the lower **Add** button to select it as the **Weight variable** and obtain the screen shown below.

X

ID and Weight Variables

Variables in data:

PSU	Add >>	Level 2 ID variable:
WEIGHT	<< Remove	PSU
AGE		
AGE_GM	Add >>	Level 3 ID variable:
SEX	<< Remove	
FULLTIME		
YR2_DEP	Add >>	Weight variable:
WHITEOTH	<< Remove	WEIGHT
BLACK		
HISP		
YOUNG	Add >>	
MIDDLE	<< Remove	
OLD		

<< Previous Next >> Cancel OK

To build syntax, proceed to the Random Variables screen and click the Finish button

Click on the **Next** button to load the **Distribution and Links** dialog box. Select **Binomial** from the **Distribution type** dropdown list box. By default, the logit link function is selected. Keep the other default settings unchanged as shown below, and click on the **Next** button.

X

Distributions and Links

Distribution type: **Binomial**

Link function: **Logit**

Include intercept? Yes No

Dispersion parameter Yes Fixed value: **1.0**

Estimate scale?

<< Previous Next >> Cancel OK

To build syntax, proceed to the Random Variables screen and click the Finish button

On the **Dependent and Independent Variables** dialog box screen, first select YR2_DEP and click on the upper **Add** button to define it as the **Dependent variable**. Then, select SEX and the other predictors and click on the **Continuous** button to add these variables in the **Independent variables** list box as shown below.

Dependent and Independent Variables

Variables in data:

- PSU
- WEIGHT
- AGE
- AGE_GM
- SEX
- FULLTIME
- YR2_DEP
- WHITEOTH
- BLACK
- HISP
- YOUNG
- MIDDLE
- OLD

Dependent variable: YR2_DEP

Independent variables: AGE_GM, FULLTIME, SEX, BLACK, YOUNG, MIDDLE

Buttons: Add >>, << Remove, Continuous >>, Categorical >>, << Remove

Navigation: << Previous, Next >>, Cancel, OK

To build syntax, proceed to the Random Variables screen and click the Finish button.

Random Variables

Variables in data:

- PSU
- WEIGHT
- AGE
- AGE_GM
- SEX
- FULLTIME
- YR2_DEP
- WHITEOTH
- BLACK
- HISP
- YOUNG
- MIDDLE
- OLD

Random Level 2: AGE_GM

Random Level 3:

Number of interactions: 0

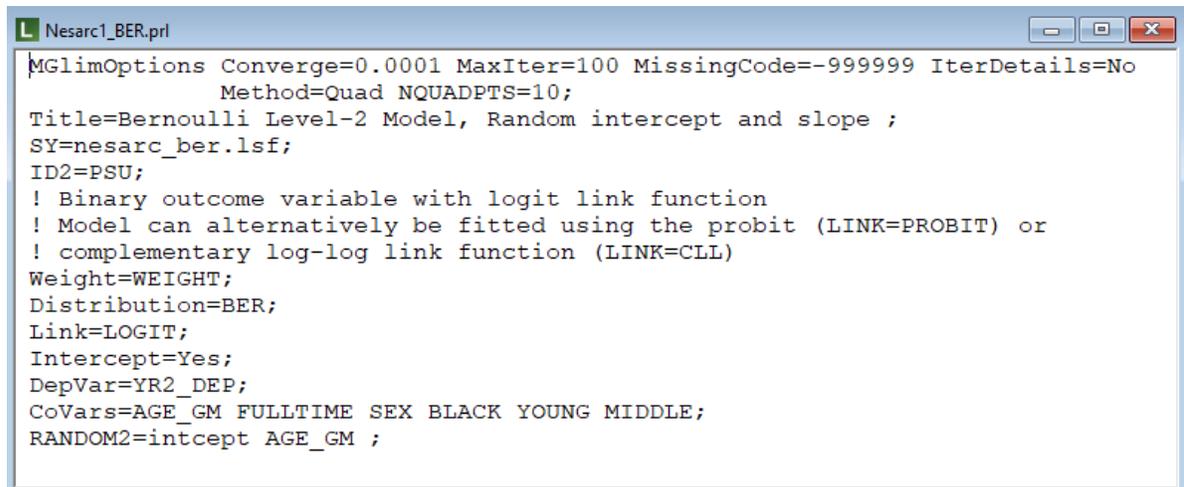
Buttons: Add >>, << Remove, Intercept (checked), Add >>, << Remove

Navigation: << Previous, Finish, Cancel, OK

To build syntax, click the Finish button.

Click on the **Next** button to proceed to the **Random Variables** dialog box once these settings have been defined. Keep the **Intercept** check box checked so as to include a level-2 intercept and add AGE_GM to the **Random Level-2** field to allow this slope to vary randomly over PSUs.

Click on the **Finish** button to generate the PRELIS syntax file (.prl) that corresponds to the above settings. Select the **File, Save As** option, and provide a name (**nesarc1_BER.prl**) for the model specification file. The default folder for the syntax to be saved in is the same folder used for the data file.



```
MGLIMOptions Converge=0.0001 MaxIter=100 MissingCode=-999999 IterDetails=No
Method=Quad NQUADPTS=10;
Title=Bernoulli Level-2 Model, Random intercept and slope ;
SY=nesarc_ber.lsf;
ID2=PSU;
! Binary outcome variable with logit link function
! Model can alternatively be fitted using the probit (LINK=PROBIT) or
! complementary log-log link function (LINK=CLL)
Weight=WEIGHT;
Distribution=BER;
Link=LOGIT;
Intercept=Yes;
DepVar=YR2_DEP;
CoVars=AGE_GM FULLTIME SEX BLACK YOUNG MIDDLE;
RANDOM2=intcept AGE_GM ;
```

The syntax file

The syntax file contains the following information:

- The MGLIMOptions keyword requests the MGLIM module to run. The first two lines, together with the Title line, correspond to the settings entered in the **Title and Options** dialog box.
- The SY line indicates the location and name of the *.lsf data file.
- PSU is the level-2 ID variable, while Weight corresponds with the weight variable. These are defined in the **ID and Weights** dialog box.
- The syntax lines for Distribution, Link and level-1 Intercept are set up in the **Distribution and Links** dialog box.
- The DepVar line, which represents the dependent variable and the CoVars line, which represents the covariate variable, are defined in the **Dependent and Independent Variables** dialog box.
- Finally, the RANDOM2 syntax line corresponds to the **Random Variables** dialog box.

Understanding how the syntax works enables the user to make changes directly to the syntax file. Run the analysis by selecting the **Run PRELIS** button to generate the output file. The output file has the same file name as the syntax file with a different extension **.out**. It is saved in the same folder as the syntax file.


```

=====
| Descriptive statistics for all the variables in the model |
=====
Variable          Minimum      Maximum      Mean      Standard
-----          -
YR2_DEP1          0.0000      1.0000      0.9441    0.2297
YR2_DEP2          0.0000      1.0000      0.0559    0.2297
intcept           1.0000      1.0000      1.0000    0.0000
AGE_GM            -28.3570    51.6430     -0.0002   18.1725
FULLTIME          0.0000      1.0000      0.5172    0.4997
SEX               0.0000      1.0000      0.5713    0.4949
BLACK             0.0000      1.0000      0.1978    0.3984
YOUNG             0.0000      1.0000      0.3020    0.4591
MIDDLE            0.0000      1.0000      0.3036    0.4598

```

Results for the model without any random effects

Descriptive statistics are followed by the results for the model without any random effects. These parameters are used in the initial step of the iterative algorithm. They are obtained by ordinary weighted least squares (WLS) regression. The goodness of WLS fit statistics are also given as shown below.

```

=====
| Results for the model without any random effects |
=====

Goodness of fit statistics

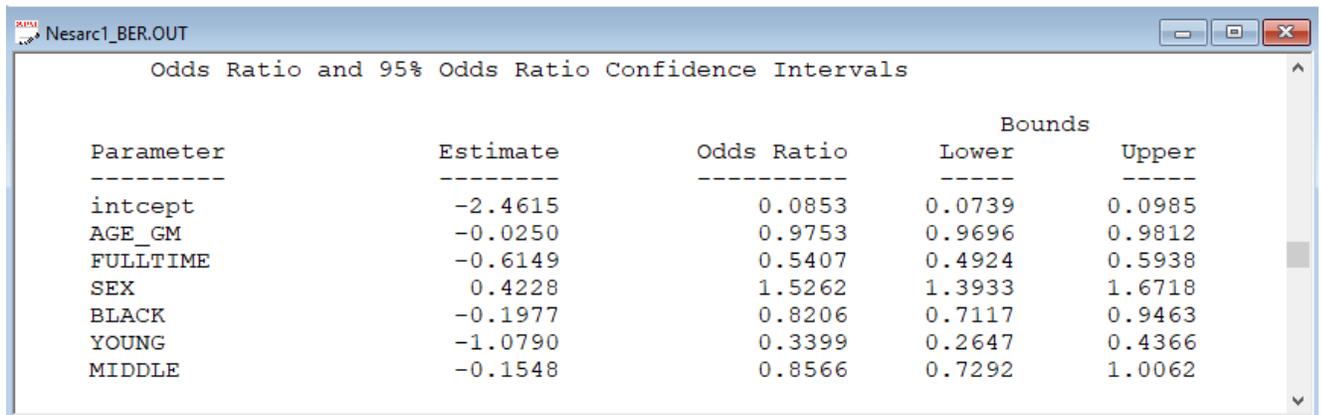
Statistic          Value          DF          Ratio
-----          -
Likelihood Ratio Chi-square  239368.4457    41842      5.7208
Pearson Chi-square    845438.9716    41842      20.2055
Log Likelihood        -8575.3217
Akaike Information Criterion  17164.6434
Schwarz Criterion    17225.1362

Estimated regression weights

Parameter          Estimate      Standard      z Value      P Value
-----          -
intcept            -2.4615      0.0733      -33.5939     0.0000
AGE_GM             -0.0250      0.0030      -8.2058     0.0000
FULLTIME           -0.6149      0.0478     -12.8738     0.0000
SEX                0.4228      0.0465      9.0971     0.0000
BLACK              -0.1977      0.0727     -2.7201     0.0065
YOUNG              -1.0790      0.1276     -8.4535     0.0000
MIDDLE             -0.1548      0.0822     -1.8846     0.0595

```

This is followed by odds ratios and 95% confidence intervals for the odds ratios.



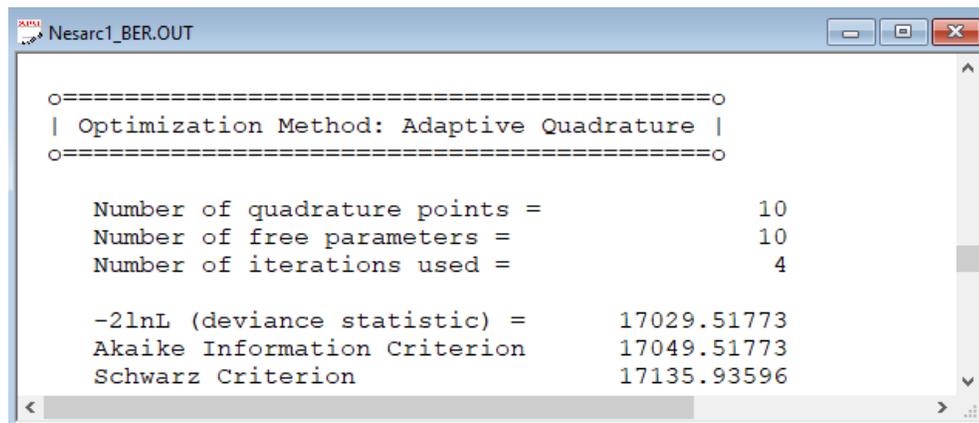
Parameter	Estimate	Odds Ratio	Bounds	
			Lower	Upper
intcept	-2.4615	0.0853	0.0739	0.0985
AGE_GM	-0.0250	0.9753	0.9696	0.9812
FULLTIME	-0.6149	0.5407	0.4924	0.5938
SEX	0.4228	1.5262	1.3933	1.6718
BLACK	-0.1977	0.8206	0.7117	0.9463
YOUNG	-1.0790	0.3399	0.2647	0.4366
MIDDLE	-0.1548	0.8566	0.7292	1.0062

Results for the model with fixed and random effects

Number of iterations and fit statistics

The total number of (macro) iterations is reported. As shown below, there are 58 iterations to get the converged results.

In addition to the likelihood function value at convergence, a number of related statistical measures for assessing model adequacy are available. The most common of these are the likelihood ratio test, Pearson chi-square, and Akaike's and Schwarz's criteria. Both the Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC) are functions of the number of estimated parameters, and therefore "penalize" models with large numbers of parameters. In the LISREL output file, all three of these are reported. A chi-square scale factor, with which a chi-square value obtained from the difference between two deviance statistics should be multiplied to yield a corrected chi-square statistic in the case of a weighted analysis, may also be found in this section.



```

=====o
| Optimization Method: Adaptive Quadrature |
=====o

Number of quadrature points =           10
Number of free parameters =           10
Number of iterations used =              4

-2lnL (deviance statistic) =          17029.51773
Akaike Information Criterion          17049.51773
Schwarz Criterion                     17135.93596

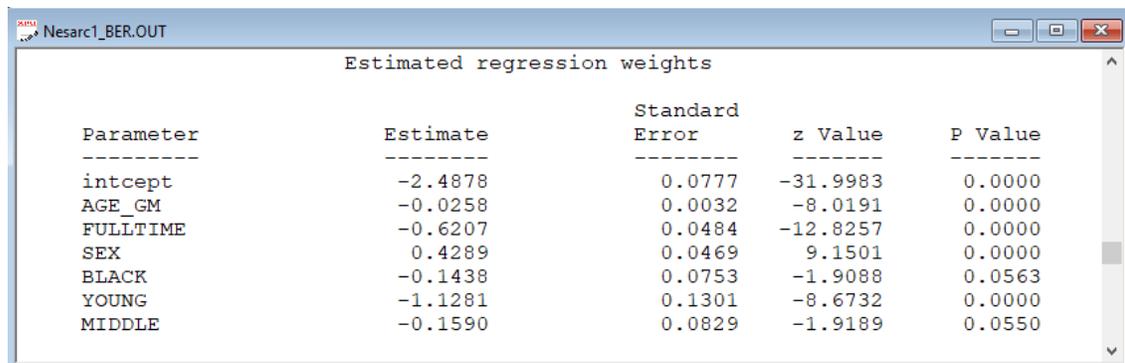
```

- The Pearson Chi-square is defined as $\chi^2_P = \sum_{i=1}^N \sum_{j=1}^{n_i} \sum_{k=1}^{n_{ij}} \frac{w_{ijk} (y_{ijk} - \hat{\mu}_{ijk})^2}{\hat{\sigma}^2(y_{ijk})}$.
- The deviance is defined as $-2\ln L$. For a pair of nested models, the difference in $-2\ln L$ values has a χ^2 distribution, with degrees of freedom equal to the difference in number of parameters estimated in the models compared.

- The AIC was originally proposed for time-series models, but is also used in regression. It is defined as $-2\ln L + 2r$, where r denotes the number of parameters estimated in the model. The model with minimum AIC, in a set of nested models, will be the most parsimonious according to this criterion.
- The SBC is defined as $-2\ln L + r \log n$, where n denotes the number of units at the highest level of the hierarchy. A smaller value of this criterion would indicate the most parsimonious of the models being compared.

Estimated regression weights

The output describing the estimated regression weights after fit statistics is shown next. The estimates are shown in the column with heading Estimate and correspond to the coefficients β_0, β_1 etc. in the model specification. From the z-values and associated exceedance probabilities, we see that most of the estimates are highly significant at 10% level.



Parameter	Estimate	Standard Error	z Value	P Value
intcept	-2.4878	0.0777	-31.9983	0.0000
AGE_GM	-0.0258	0.0032	-8.0191	0.0000
FULLTIME	-0.6207	0.0484	-12.8257	0.0000
SEX	0.4289	0.0469	9.1501	0.0000
BLACK	-0.1438	0.0753	-1.9088	0.0563
YOUNG	-1.1281	0.1301	-8.6732	0.0000
MIDDLE	-0.1590	0.0829	-1.9189	0.0550

The estimated intercept is -2.4878, which is the average logit. The estimated coefficients associated with gender (SEX) is 0.4289, which indicates that the female respondents (SEX = 1) have a larger $\hat{\eta}$. The estimate for the indicator of race (BLACK) shows that white clients have higher $\hat{\eta}$ values. Younger respondents have lower $\hat{\eta}$ values than older respondents judging by the size of the estimates for the two variables YOUNG and MIDDLE. To describe the η 's in a more accessible way to readers of reports, we need the link functions to transform them into probabilities.

Interpreting estimated regression weights by using link function

We consider four respondents: all white (BLACK=0) of AGE equal to the grand mean. As the grand mean age is 46.357, both respondents would thus have a value of 1 on the variable MIDDLE and a value of 0 on the other age-related variable YOUNG. This implies that the 4 respondents only differ on gender and employment. We substitute the regression weights and obtain the function for $\hat{\eta}_{ij}$

$$\begin{aligned}\hat{\eta}_{ij} &= \hat{b}_{0i} + \hat{b}_{3i} \times (\text{SEX})_{ij} + \hat{b}_{2i} \times (\text{FULLTIME})_{ij} \\ &= -2.4878 + 0.4289 \times (\text{SEX})_{ij} - 0.6207 \times (\text{FULLTIME})_{ij}\end{aligned}$$

By substituting the values of gender and employment status, we obtain four estimates of η_{ij} . Next, we transform the $\hat{\eta}_{ij}$'s into corresponding probabilities by using the logit link function

$$\text{Prob}(\text{DEPR}_{ij} = 1) = \frac{e^{\hat{\eta}_{ij}}}{1 + e^{\hat{\eta}_{ij}}} = \frac{1}{1 + e^{-\hat{\eta}_{ij}}} =$$

to obtain the results in the table below.

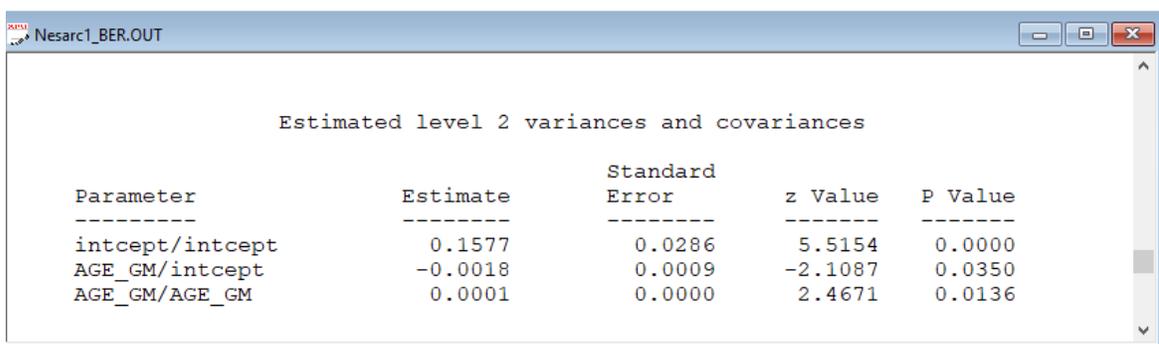
Respondent	Code	$\hat{\eta}$	Prob (DEPR = 1)
Male, employed	sex = 0, fulltime = 1	-3.1085	4.28%
Male, not employed	sex = 0, fulltime = 0	-2.4878	7.67%
Female, employed	sex = 1, fulltime = 1	-2.6796	6.42%
Female, not employed	sex = 1, fulltime = 0	-2.0589	11.32%

We can conclude that the estimated probability for a unemployed female is the highest at 11.32%. From the results, we conclude that females are more likely to have an episode, and this risk increases if they are not employed full time.

Group	Code	$\hat{\eta}$	Prob (DEPR = 1)
Black, male	sex = 0, race_d = 0	0.1018	47.53%
Black, female	sex = 1, race_d = 0	0.6848	66.48%
White, male	sex = 0, race_d = 1	-0.7450	32.19%
White, female	sex = 1, race_d = 1	0.0388	50.97%

Estimated level-2 variance

The output for the estimated level-2 variance is shown in the image below. The p value of intercept shows the probability of having an episode within the time period of study differs significantly from PSU to PSU (the level-2 units).



Parameter	Estimate	Standard Error	z Value	P Value
intcept/intcept	0.1577	0.0286	5.5154	0.0000
AGE_GM/intcept	-0.0018	0.0009	-2.1087	0.0350
AGE_GM/AGE_GM	0.0001	0.0000	2.4671	0.0136

6. Alternative model

Alternatively, we can fit a model with probit link function to these data. The syntax for this model is given in `nesarc2_ber.prl`.

```
Nesarc2_BER.prl
MGLimOptions Converge=0.0001 MaxIter=100 MissingCode=-999999 IterI^
Method=Quad NQUADPTS=10;
Title=Bernoulli Level-2 Model, random intercept model;
SY=nesarc_ber.lsf;
ID2=PSU;
! Binary outcome variable with Probit link function
! Model can alternatively be fitted using the probit (LINK=PROBIT)
! complementary log-log link function (LINK=CLL)
Weight=WEIGHT;
Distribution=BER;
Link=PROBIT;
Intercept=Yes;
DepVar=YR2_DEP;
Covars=AGE_GM SEX FULLTIME BLACK YOUNG MIDDLE;
RANDOM2=intcept;
```

From the results of this analysis, we see higher fit statistics, leading us to conclude that the previous model fitted the data better. Though the estimates are obviously different, we note that gender is again the only predictor with a positive estimated regression weight.

```
Nesarc2_BER.OUT
=====o
| Optimization Method: Adaptive Quadrature |
=====o

Number of quadrature points =          10
Number of free parameters =           8
Number of iterations used =           2

-2lnL (deviance statistic) =      17052.87648
Akaike Information Criterion      17068.87648
Schwarz Criterion                 17138.01107

Estimated regression weights

Parameter      Estimate      Standard      z Value      P Value
-----      -
intcept        -1.4350        0.0364       -39.4604     0.0000
AGE_GM         -0.0116        0.0014       -8.1080     0.0000
SEX            0.2057        0.0217        9.4626     0.0000
FULLTIME       -0.2865        0.0227       -12.5988     0.0000
BLACK          -0.0670        0.0348       -1.9236     0.0544
YOUNG          -0.4892        0.0595       -8.2174     0.0000
MIDDLE         -0.0629        0.0389       -1.6154     0.1062
```

The final output is the population-average results. The regression parameters in multilevel generalized linear models have the “unit-specific” or conditional interpretation, in contrast to the “population-average” or marginal estimates that represent the unconditional covariate effects. LISREL uses numerical quadrature to obtain population-average estimates from their unit-specific

counterparts in models with multiple random effects. Standard errors for the population-average estimates are derived using the delta method.

Under the model we fitted, the predicted probability for case ij , given u_{0j} , would be

$$E(Y_{ij} | u_{0j}) = \frac{1}{1 + \exp \left\{ - \left(\beta_0 + \beta_1 \times AGE_GM_{ij} + \beta_2 \times FULLTIME_{ij} + \beta_3 \times SEX_{ij} + \beta_4 \times BLACK_{ij} + \beta_5 \times YOUNG_{ij} + \beta_6 \times MIDDLE_{ij} + u_{0j} \right) \right\}}.$$

while the population average model would be

$$E(Y_{ij} |) = \frac{1}{1 + \exp \left\{ - \left(\beta_0 + \beta_1 \times AGE_GM_{ij} + \beta_2 \times FULLTIME_{ij} + \beta_3 \times SEX_{ij} + \beta_4 \times BLACK_{ij} + \beta_5 \times YOUNG_{ij} + \beta_6 \times MIDDLE_{ij} \right) \right\}}.$$

Users will need to take care in choosing unit-specific versus population-average results for their research. The choice will depend on the specific research questions that are of interest. If one were primarily interested in how a change in one of the predictors, for example FULLTIME, can be expected to affect a particular individual PSU's mean, one would use the unit-specific model. If one were interested in how a change in FULLTIME can be expected to affect the overall population mean, one would use the population-average model.