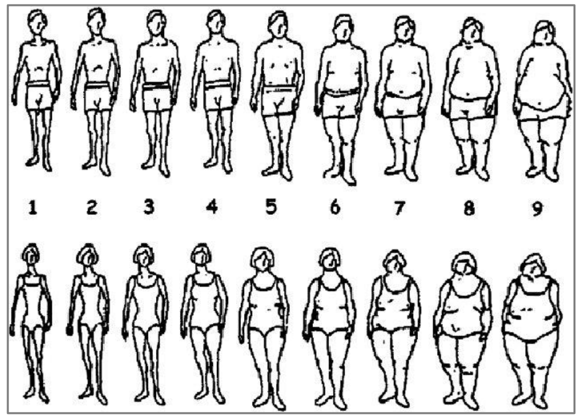
Example 5a: Multivariate General(ized) Linear Models for Difference Scores
Part 1 in SAS MIXED and STATA MIXED; Part 2 also in Mplus and STATA SEM
(complete syntax and output available for SAS and STATA electronically)

The data for this example were collected as part of this a study reported here: Gervais, S. J., Vescio, T. K., & Allen, J. (2011). When what you see if what you get: The consequences of the objectifying gaze for women and men. *Psychology of Women Quarterly*, *35*(1), 5-17.



One minor question in this paper focused on gender differences in how discrepant the people felt their bodies were from their own ideals. To measure this, participants completed the Figure Rating Scale (Stunkard, Sorensen, & Schulsinger, 1983; see image at right), which has pictures of nine bodies varying from extremely thin (1) to extremely overweight (9). Participants provided one rating for their *ideal* body and another for their *actual* body. The present example uses the ideal and actual ratings for 78 men and 67 women to demonstrate how to examine gender differences in body discrepancy using two analytic strategies.

In Part 1 we will estimate multivariate general linear models (GLMs) in SAS MIXED and STATA MIXED with conditional normal distributions using residual maximum likelihood (REML), and we will text fixed effects using Satterthwaite denominator degrees of freedom. Note that STATA provides incorrect AIC and BIC values using REML (it counts all parameters instead of variance parameters only), so those values are not referred to below. We will show how these multivariate models predicting actual and ideal ratings are directly equivalent to univariate GLMs predicting each person's body discrepancy difference score (with residual denominator degrees of freedom instead). We will also predict the discrepancy as an ordinal outcome in SAS GLIMMIX and STATA GOLOGIT2 instead (using maximum likelihood in both programs as required; without denominator degrees of freedom in SAS for comparability).

In Part 2, we will estimate the same multivariate general and generalized linear models using path analysis in Mplus and STATA SEM (using maximum likelihood without denominator degrees of freedom as required by the programs).

Part 1: Multivariate General Linear Models via Univariate MIXED Software

Original data in <u>wide</u> format (was one row per person, rating outcomes in separate columns):

	Person ID Number	Gender 0=M, 1=W	Gender	Actual Body Rating	Ideal Body Rating	Actual - Ideal Rating
1	100	0	0.Men	1	3	2
2	101	0	0.Men	2	3	1

New data in <u>stacked</u> format (one row per outcome per person) after transformation code below:

	Person ID Number	MvsW 0=M, 1=W	Gender	Actual4	Ideal4	DV: Body Rating Type	dvA: Is Actual (0=N, 1=Y)	dvI: Is Ideal (0=N, 1=Y)	dvD: Is Actual-Ideal	Body Rating Outcome
1	100	0	0.Men	-3	-1	1.Actual	1	0	0	1
2	100	0	0.Men	-3	-1	2.Ideal	0	1	0	3
3	100	0	0.Men	-3	-1	3.Diff	0	0	1	2
4	101	0	0.Men	-2	-1	1.Actual	1	0	0	2
5	101	0	0.Men	-2	-1	2.Ideal	0	1	0	3
6	101	0	0.Men	-2	-1	3.Diff	0	0	1	1

STATA Syntax for Importing and Stacking Wide into Univariate (now one row <u>per outcome per person</u>):

```
// Define global variable for file location to be replaced in code below
   global filesave "C:\Dropbox\20_PSQF7375_Generalized\PSQF7375_Generalized_Example5a"

// Import example 5a multivariate data and sort by gender
   use "$filesave\Example5aWide.dta", clear
   sort gender
```

```
// Center actual and ideal to use as predictors later
   gen Actual4=actual-4
   gen Ideal4=ideal-4

// Rename variables with numeric suffix to use with reshape (old)(new)
   rename (actual ideal diff) (rating1 rating2 rating3)
   rename (mvsw) (MvsW) // Rename for consistency with SAS syntax

// Stack data: list multivariate variables first, i(higher index) j(repeated)
   reshape long rating, i(personid) j(DV)

// Create value labels and apply to dv
   label define dvlabel 1 "1.Actual" 2 "2.Ideal" 3 "3.Diff"
   label values DV dvlabel

// Create dummy codes
   gen dvA=0
   gen dvI=0
   gen dvD=0
   recode dvA (0=1) if DV==1
   recode dvI (0=1) if DV==2
   recode dvD (0=1) if DV==3

// Label new variables
   label variable personid "Person ID Number"
   label variable MvsW     "MvsW 0=M, 1=W"
   label variable DV       "DV: Body Rating Type"
   label variable dvA      "dvA: Is Actual(0=no, 1=yes)"
   label variable dvI      "dvI: Is Ideal (0=no, 1=yes)"
   label variable dvD      "dvD: Is Actual-Ideal (0=no, 1=yes)"
   label variable rating   "Body Rating Outcome"
```

SAS Syntax for Importing and Stacking Wide into Univariate (now one row per outcome per person):

```
* Define global variable for file location to be replaced in code below;
%LET filesave= C:\Dropbox\20_PSQF7375_Generalized\PSQF7375_Generalized_Example5a;
* Location for SAS files for these models (uses macro variable filesave);
LIBNAME filesave "&filesave.";

* Import example 5a multivariate data into work library and sort it by gender;
DATA work.Example5aWide; SET filesave.Example5aWide; RUN;
PROC SORT DATA=work.Example5aWide; BY Gender; RUN; * Women start at 84;

* Import example 5a multivariate data into work library and stack it;
DATA work.Example5a; SET filesave.Example5aWide;
     Actual4=Actual-4; Ideal4=Ideal-4;
     DV="1.Actual"; dvA=1; dvI=0; dvD=0; rating=Actual; OUTPUT;
     DV="2.Ideal";  dvA=0; dvI=1; dvD=0; rating=Ideal;  OUTPUT;
     DV="3.Diff";   dvA=0; dvI=0; dvD=1; rating=Diff;   OUTPUT;
     LABEL PersonID= "Person ID Number"
           MvsW=     "MvsW 0=M, 1=W"
           DV=       "DV: Body Rating Type"
           dvA=      "dvA: Is Actual (0=N, 1=Y)"
           dvI=      "dvI: Is Ideal (0=N, 1=Y)"
           dvD=      "dvD: Is Actual-Ideal"
           rating=   "Body Rating Outcome";
      DROP Actual Ideal Diff; * Remove old multivariate outcomes;
RUN;
PROC SORT DATA=work.Example5a; BY DV PersonID; RUN;
```

STATA Syntax for Data Description:

```
display as result "STATA Descriptives for Body Ratings by Gender"
bysort DV: tabulate gender rating

display as result "STATA Empty Models Predicting Each Body Rating Type by Gender"
display as result "STATA GLM to Check Pearson Chi-Square / DF"
bysort DV: glm rating c.mvsw, link(identity) family(gaussian
```

SAS Syntax and Output for Data Description:

```
TITLE "SAS Descriptives for Body Ratings by Gender";
PROC FREQ DATA=work.Example5a; BY DV; TABLE Gender*rating / NOROW NOCOL NOPERCENT; RUN;
TITLE;
```

Table of Gender by Actual

Gender	Actual(Actual Body Rating)									
Frequency	1	2	3	4	5	6	7	8	9	Total
0.Men	6	9	19	10	12	14	4	3	1	78
1.Women	1	8	11	9	21	6	5	4	2	67
Total	7	17	30	19	33	20	9	7	3	145

Table of Gender by Ideal

Gender	Ideal(Ideal Body Rating)					
Frequency	2	3	4	5	6	Total
0.Men	1	18	30	24	5	78
1.Women	2	22	30	10	3	67
Total	3	40	60	34	8	145

Table of Gender by Diff

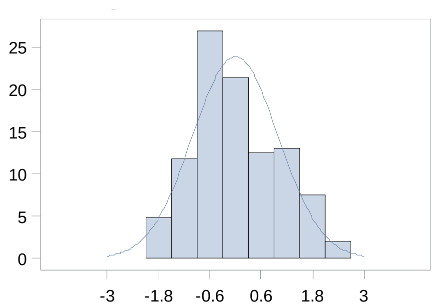
Gender	Diff(Actual - Ideal Rating)						
Frequency	-3	-2	-1	0	1	2	Total
0.Men	2	4	22	20	24	6	78
1.Women	5	10	27	17	8	0	67
Total	7	14	49	37	32	6	145

It looks like there are more men whose ideal is the same as their actual (Diff = 0) or whose ideal is greater than their actual (Diff = 1 or 2).

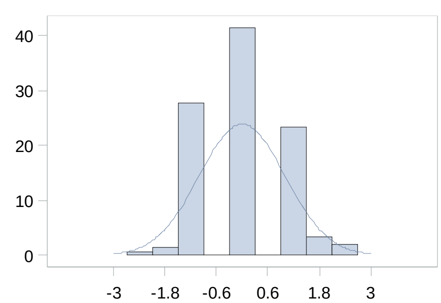
Before examining the models to support this assertion, let's see how plausible a conditional normal distribution is for each rating outcome: Actual, Idea, and Difference.

```
TITLE1 "SAS Empty Models Predicting Each Body Rating Type by Gender";
TITLE2 "SAS GLIMMIX to Check Pearson Chi-Square / DF";
PROC GLIMMIX DATA=work.Example5a NOCLPRINT NAMELEN=100 METHOD=MSPL;* PLOTS=ALL;
     BY DV;
     MODEL rating = MvsW / SOLUTION LINK=IDENTITY DIST=NORMAL DDFM=NONE;
RUN; TITLE1; TITLE2;
```

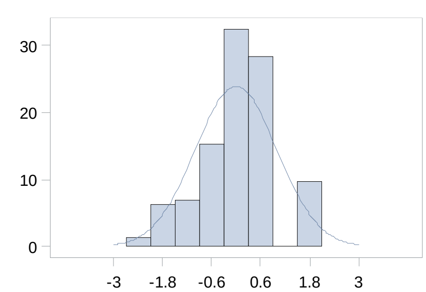
Actual Pearson Residuals:
$\chi^2/DF = 3.52$



Ideal Pearson Residuals:
$\chi^2/DF = 0.79$



Difference Pearson Residuals:
$\chi^2/DF = 1.24$



The Pearson residuals for the actual body rating may have some over-dispersion, but the Pearson residuals for the ideal body rating and for their difference (actual – ideal) seem plausibly normal. So let's start with multivariate general linear models—predicting two outcomes simultaneously using an identity link for each and a conditional multivariate normal distribution—with gender as a predictor of each outcome.

Model 1a Predicting Actual and Ideal Ratings with DV-Specific Intercepts and Same R Matrix by Gender:

$$\widehat{Rating}_{it} = \beta_{00}(Actual_{it}) + \beta_{01}(Ideal_{it}) + \beta_{10}(Actual_{it})(MvsW_i) + \beta_{11}(Ideal_{it})(MvsW_i)$$

```
display as result "STATA Multivariate GLM Predict Actual and Ideal with DV-Specific Intercepts"
display as result "STATA Using REML in MIXED with Unstructured R Matrix Same By Gender"
mixed rating c.dvA c.dvI c.dvA#c.MvsW c.dvI#c.MvsW if dvD==0,  /// Predict only actual and ideal
         noconstant /// Remove fixed intercept
         || personid: , noconstant variance reml residuals(unstructured,t(DV)) ///
         dfmethod(satterthwaite) dftable(pvalue)
estat wcorrelation, covariance,  // R matrix
estat wcorrelation,              // RCORR matrix
lincom c.dvA*1  + c.dvI*0 + c.dvA#MvsW*0  + c.dvI#MvsW*0, small // Actual Men
lincom c.dvA*1  + c.dvI*0 + c.dvA#MvsW*1  + c.dvI#MvsW*0, small // Actual Women
lincom c.dvA*0  + c.dvI*1 + c.dvA#MvsW*0  + c.dvI#MvsW*0, small // Ideal Men
lincom c.dvA*0  + c.dvI*1 + c.dvA#MvsW*0  + c.dvI#MvsW*1, small // Ideal Women
lincom                      c.dvA#MvsW*1  + c.dvI#MvsW*0, small // MvsW for Actual
lincom                      c.dvA#MvsW*0  + c.dvI#MvsW*1, small // MvsW for Ideal
lincom c.dvA*-1 + c.dvI*1 + c.dvA#MvsW*0  + c.dvI#MvsW*0, small // AvsI for Men
lincom c.dvA*-1 + c.dvI*1 + c.dvA#MvsW*-1 + c.dvI#MvsW*1, small // AvsI for Women
lincom                      c.dvA#MvsW*-1 + c.dvI#MvsW*1, small // AvsI Gender Diff

TITLE1 "SAS Multivariate GLM Predicting Actual and Ideal with DV-Specific Intercepts";
TITLE2 "SAS Using REML in MIXED with Unstructured R Matrix Same By Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvD=0;              * Predict only actual and ideal;
     CLASS PersonID DV Gender;  * NOINT --> No general reference DV;
     MODEL rating = dvA dvI dvA*MvsW dvI*MvsW / NOINT SOLUTION DDFM=Satterthwaite NOTEST;
     REPEATED DV / R RCORR TYPE=UN SUBJECT=PersonID;
     ESTIMATE "Actual Men"        dvA  1 dvI 0 dvA*MvsW  0 dvI*MvsW 0;
     ESTIMATE "Actual Women"      dvA  1 dvI 0 dvA*MvsW  1 dvI*MvsW 0;
     ESTIMATE "Ideal Men"         dvA  0 dvI 1 dvA*MvsW  0 dvI*MvsW 0;
     ESTIMATE "Ideal Women"       dvA  0 dvI 1 dvA*MvsW  0 dvI*MvsW 1;
     ESTIMATE "MvsW for Actual"                dvA*MvsW  1 dvI*MvsW 0;
     ESTIMATE "MvsW for Ideal"                 dvA*MvsW  0 dvI*MvsW 1;
     ESTIMATE "AvsI for Men"      dvA -1 dvI 1 dvA*MvsW  0 dvI*MvsW 0;
     ESTIMATE "AvsI for Women"    dvA -1 dvI 1 dvA*MvsW -1 dvI*MvsW 1;
     ESTIMATE "AvsI Gender Diff"               dvA*MvsW -1 dvI*MvsW 1;
RUN; TITLE2;
```

SAS Output for Model 1a:

Iteration History

Iteration	Evaluations	-2 Res Log Like	Criterion
0	1	1052.14958568	
1	1	709.74148341	0.00000000

For your homework using SAS, get your −2LL value from this table to get two digits after the decimal.

Estimated R Matrix for PersonID 100

Row	Col1	Col2
1	3.5706	1.5528
2	1.5528	0.7972

Estimated R Correlation Matrix for PersonID 100

Row	Col1	Col2
1	1.0000	0.9204
2	0.9204	1.0000

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr Z	
UN(1,1)	PersonID	3.5706	0.4223	8.46	<.0001	Actual Residual Variance
UN(2,1)	PersonID	1.5528	0.1917	8.10	<.0001	Actual-Ideal Residual Covariance
UN(2,2)	PersonID	0.7972	0.09427	8.46	<.0001	Ideal Residual Variance

Fit Statistics

-2 Res Log Likelihood	709.74
AIC (Smaller is Better)	715.7
AICC (Smaller is Better)	715.8
BIC (Smaller is Better)	724.7

We will see these same fit statistics in the models after the next one (after Model 1b).

```
                    Solution for Fixed Effects
                          Standard
Effect       Estimate       Error      DF    t Value    Pr > |t|
dvA            4.1795      0.2140     143      19.53      <.0001  B00 Actual Intercept
dvI            4.1795      0.1011     143      41.34      <.0001  B01  Ideal Intercept
dvA*MvsW       0.4772      0.3148     143       1.52      0.1317  B10 Actual Gender Diff
dvI*MvsW      -0.3287      0.1487     143      -2.21      0.0287  B11  Ideal Gender Diff

                                 Estimates → Would be Table 1 in results
                                  Standard
Label                 Estimate       Error      DF    t Value    Pr > |t|
Actual Men              4.1795      0.2140     143      19.53      <.0001  B00
Actual Women            4.6567      0.2309     143      20.17      <.0001  B00+B10
Ideal Men               4.1795      0.1011     143      41.34      <.0001  B01
Ideal Women             3.8507      0.1091     143      35.30      <.0001  B01+B11
MvsW for Actual         0.4772      0.3148     143       1.52      0.1317  B10
MvsW for Ideal         -0.3287      0.1487     143      -2.21      0.0287  B11
AvsI for Men           3.2E-14      0.1272     143       0.00      1.0000  B01-B00
AvsI for Women         -0.8060      0.1372     143      -5.87      <.0001  B01+B11-B00-B10
AvsI Gender Diff       -0.8060      0.1871     143      -4.31      <.0001  B11-B10
```

Model 1b Testing Different R Matrix by Gender:

```
display as result "STATA Using REML in MIXED with Unstructured R Matrix Separate By Gender"
mixed rating c.dvA c.dvI c.dvA#c.MvsW c.dvI#c.MvsW if dvD==0,  /// Predict only actual and ideal
         noconstant /// Remove fixed intercept
         || personid: , noconstant variance reml residuals(unstructured,t(DV)by(MvsW)) ///
         dfmethod(satterthwaite) dftable(pvalue) // by: R matrix separate by gender now
estat wcorrelation, covariance at(personid=100)  // R matrix for Men
estat wcorrelation, at(personid=100)             // RCORR matrix for Men
estat wcorrelation, covariance at(personid=103)  // R matrix for Women
estat wcorrelation, at(personid=103)             // RCORR matrix for Women

TITLE2 "SAS Using REML in MIXED Testing Unstructured R Matrix Seprate By Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvD=0;                 * Predict only actual and ideal;
     CLASS PersonID DV Gender;    * NOINT --> No general reference DV;
     MODEL rating = dvA dvI dvA*MvsW dvI*MvsW / NOINT SOLUTION DDFM=Satterthwaite NOTEST;
     REPEATED DV / R=1,84 RCORR=1,84 TYPE=UN SUBJECT=PersonID GROUP=Gender;
RUN; TITLE1; TITLE2;
```

SAS Output for Model 1b:

```
   Estimated R Matrix for PersonID 100           Estimated R Correlation Matrix for PersonID 100
 Row         Col1         Col2                     Row         Col1         Col2
   1       3.6817       1.5778                       1       1.0000       0.9056
   2       1.5778       0.8245                       2       0.9056       1.0000

   Estimated R Matrix for PersonID 189           Estimated R Correlation Matrix for PersonID 189
 Row         Col1         Col2                     Row         Col1         Col2
   1       3.4410       1.5237                       1       1.0000       0.9056
   2       1.5237       0.7653                       2       0.9390       1.0000

           Fit Statistics
-2 Res Log Likelihood              705.21
AIC (Smaller is Better)            717.2
AICC (Smaller is Better)           717.5
BIC (Smaller is Better)            735.1
```

Does Model 1b with separate R matrices by gender fit better than Model 1a with the same R matrix across men and women?

$-2\Delta LL$ (3) = 709.74 – 705.21 = 4.63, p = .210, so diff R matrix is not better

Model 2a Predicting Actual and Ideal Ratings with a General Intercept and Same R Matrix by Gender:

$$\widehat{Rating}_{it} = \beta_{00} + \beta_{01}(Ideal_{it}) + \beta_{10}(MvsW_i) + \beta_{11}(Ideal_{it})(MvsW_i)$$

```
display as result "STATA Multivariate GLM Predicting Actual and Ideal with a General Intercept"
display as result "STATA Using REML in MIXED with Unstructured R Matrix Same By Gender"
mixed rating c.dvI c.MvsW c.dvI#c.MvsW if dvD==0,  /// Predict only actual and ideal
         || personid: , noconstant variance reml residuals(unstructured,t(DV)) ///
         dfmethod(satterthwaite) dftable(pvalue)
estat wcorrelation, covariance,  // R matrix
estat wcorrelation,              // RCORR matrix
lincom c._cons*1  + c.dvI*0 + c.MvsW*0 + c.dvI#c.MvsW*0, small // Actual Men
lincom c._cons*1  + c.dvI*0 + c.MvsW*1 + c.dvI#c.MvsW*0, small // Actual Women
lincom c._cons*1  + c.dvI*1 + c.MvsW*0 + c.dvI#c.MvsW*0, small // Ideal Men
lincom c._cons*1  + c.dvI*1 + c.MvsW*1 + c.dvI#c.MvsW*1, small // Ideal Women
lincom                        c.MvsW*1 + c.dvI#c.MvsW*0, small // MvsW for Actual
lincom                        c.MvsW*1 + c.dvI#c.MvsW*1, small // MvsW for Ideal
lincom              c.dvI*1            + c.dvI#c.MvsW*0, small // AvsI for Men
lincom              c.dvI*1            + c.dvI#c.MvsW*1, small // AvsI for Women
lincom                                   c.dvI#c.MvsW*1, small // AvsI Gender Diff
```

```
TITLE1 "SAS Multivariate GLM Predicting Actual and Ideal with a General Intercept";
TITLE2 "SAS Using REML in MIXED with Unstructured R Matrix Same by Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvD=0;        * Predict only actual and ideal;
     CLASS PersonID DV; * Actual is reference DV;
     MODEL rating = dvI MvsW dvI*MvsW / SOLUTION DDFM=Satterthwaite NOTEST;
     REPEATED DV / R RCORR TYPE=UN SUBJECT=PersonID;
     ESTIMATE "Actual Men"       intercept 1 dvI 0 MvsW 0 dvI*MvsW 0;
     ESTIMATE "Actual Women"     intercept 1 dvI 0 MvsW 1 dvI*MvsW 0;
     ESTIMATE "Ideal Men"        intercept 1 dvI 1 MvsW 0 dvI*MvsW 0;
     ESTIMATE "Ideal Women"      intercept 1 dvI 1 MvsW 1 dvI*MvsW 1;
     ESTIMATE "MvsW for Actual"                    MvsW 1 dvI*MvsW 0;
     ESTIMATE "MvsW for Ideal"                     MvsW 1 dvI*MvsW 1;
     ESTIMATE "AvsI for Men"                 dvI 1        dvI*MvsW 0;
     ESTIMATE "AvsI for Women"               dvI 1        dvI*MvsW 1;
     ESTIMATE "AvsI Gender Diff"                          dvI*MvsW 1;
RUN; TITLE1; TITLE2;
```

SAS Output for Model 2a—is an equivalent re-parameterization of Model 1a, but in 2a below differences in body ratings are given directly by the model fixed effects for dvI instead:

Estimated R Matrix for PersonID 100

Row	Col1	Col2
1	3.5706	1.5528
2	1.5528	0.7972

Estimated R Correlation Matrix for PersonID 100

Row	Col1	Col2
1	1.0000	0.9204
2	0.9204	1.0000

Fit Statistics

-2 Res Log Likelihood	709.74
AIC (Smaller is Better)	715.7
AICC (Smaller is Better)	715.8
BIC (Smaller is Better)	724.7

Model 2a fits the same as Model 1a because they only differ in their intercept style: DV-specific in 1a versus general in 2a .

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|	
Intercept	4.1795	0.2140	143	19.53	<.0001	B00 Actual Intercept
dvI	-999E-16	0.1272	143	-0.00	1.0000	B01 Ideal Body Diff
MvsW	0.4772	0.3148	143	1.52	0.1317	B10 Actual Gender Diff
dvI*MvsW	-0.8060	0.1871	143	-4.31	<.0001	B11 Ideal Body Diff Gender Diff

Estimates

Label	Estimate	Standard Error	DF	t Value	Pr > |t|	
Actual Men	4.1795	0.2140	143	19.53	<.0001	B00
Actual Women	4.6567	0.2309	143	20.17	<.0001	B00+B10
Ideal Men	4.1795	0.1011	143	41.34	<.0001	B00+B01
Ideal Women	3.8507	0.1091	143	35.30	<.0001	B00+B01+B10+B11
MvsW for Actual	0.4772	0.3148	143	1.52	0.1317	B10
MvsW for Ideal	-0.3287	0.1487	143	-2.21	0.0287	B10+B11
AvsI for Men	-999E-16	0.1272	143	-0.00	1.0000	B01
AvsI for Women	-0.8060	0.1372	143	-5.87	<.0001	B01+B11
AvsI Gender Diff	-0.8060	0.1871	143	-4.31	<.0001	B11

Model 3a Predicting Actual and Difference Ratings with DV-Specific Intercepts and Same R Matrix by Gender:

$$\widehat{Rating}_{it} = \beta_{00}(Actual_{it}) + \beta_{01}(Diff_{it}) + \beta_{10}(Actual_{it})(MvsW_i) + \beta_{11}(Diff_{it})(MvsW_i)$$

```
display as result "STATA Multivariate GLM Predicting Actual and Diff with DV-Specific Intercepts"
display as result "STATA Using REML in MIXED with Unstructured R Matrix Same By Gender"
mixed rating c.dvA c.dvD c.dvA#c.MvsW c.dvD#c.MvsW if dvI==0,  /// Predict only actual and diff
         noconstant /// Remove fixed intercept
         || personid: , noconstant variance reml residuals(unstructured,t(DV)) ///
         dfmethod(satterthwaite) dftable(pvalue)
estat wcorrelation, covariance,  // R matrix
estat wcorrelation,              // RCORR matrix
lincom c.dvA*1  + c.dvD*0 + c.dvA#c.MvsW*0  + c.dvD#c.MvsW*0, small // Actual Men
lincom c.dvA*1  + c.dvD*0 + c.dvA#c.MvsW*1  + c.dvD#c.MvsW*0, small // Actual Women
lincom c.dvA*1  + c.dvD*1 + c.dvA#c.MvsW*0  + c.dvD#c.MvsW*0, small // Ideal Men
lincom c.dvA*1  + c.dvD*1 + c.dvA#c.MvsW*1  + c.dvD#c.MvsW*1, small // Ideal Women
lincom                      c.dvA#c.MvsW*1  + c.dvD#c.MvsW*0, small // MvsW for Actual
lincom                      c.dvA#c.MvsW*1  + c.dvD#c.MvsW*1, small // MvsW for Ideal
lincom            c.dvD*1                   + c.dvD#c.MvsW*0, small // AvsI for Men
lincom            c.dvD*1                   + c.dvD#c.MvsW*1, small // AvsI for Women
lincom                                        c.dvD#c.MvsW*1, small // AvsI Gender Diff

TITLE1 "SAS Multivariate GLM Predicting Actual and Diff with DV-Specific Intercepts";
TITLE2 "SAS Using REML in MIXED with Unstructured R Matrix Same By Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvI=0;                * Predict only actual and diff;
     CLASS PersonID DV Gender;   * NOINT --> No general reference DV;
     MODEL rating = dvA dvD dvA*MvsW dvD*MvsW / NOINT SOLUTION DDFM=Satterthwaite NOTEST;
     REPEATED DV / R RCORR TYPE=UN SUBJECT=PersonID;
     ESTIMATE "Actual Men"         dvA 1 dvD 0 dvA*MvsW 0 dvD*MvsW 0;
     ESTIMATE "Actual Women"       dvA 1 dvD 0 dvA*MvsW 1 dvD*MvsW 0;
     ESTIMATE "Ideal Men"          dvA 1 dvD 1 dvA*MvsW 0 dvD*MvsW 0;
     ESTIMATE "Ideal Women"        dvA 1 dvD 1 dvA*MvsW 1 dvD*MvsW 1;
     ESTIMATE "MvsW for Actual"                dvA*MvsW 1 dvD*MvsW 0;
     ESTIMATE "MvsW for Ideal"                 dvA*MvsW 1 dvD*MvsW 1;
     ESTIMATE "AvsI for Men"             dvD 1            dvD*MvsW 0;
     ESTIMATE "AvsI for Women"           dvD 1            dvD*MvsW 1;
     ESTIMATE "AvsI Gender Diff"                          dvD*MvsW 1;
RUN; TITLE2;
```

SAS Output for Model 3a—is an equivalent re-parameterization of Model 1a and Model 2a:

Estimated R Matrix for PersonID 100

Row	Col1	Col2
1	3.5706	-2.0177
2	-2.0177	1.2621

Estimated R Correlation Matrix for PersonID 100

Row	Col1	Col2
1	1.0000	-0.9505
2	-0.9505	1.0000

Fit Statistics

-2 Res Log Likelihood	709.74
AIC (Smaller is Better)	715.7
AICC (Smaller is Better)	715.8
BIC (Smaller is Better)	724.7

Model 3a fits the same as 1a and 2a because ideal is a linear combination of predicting actual and their difference (with DV-specific intercepts here).

```
                  Solution for Fixed Effects
                        Standard
Effect       Estimate      Error     DF    t Value    Pr > |t|
dvA            4.1795     0.2140    143      19.53      <.0001  B00 Actual Intercept
dvD           -11E-14     0.1272    143      -0.00      1.0000  B01 Body Diff Intercept
dvA*MvsW       0.4772     0.3148    143       1.52      0.1317  B10 Actual Gender Diff
dvD*MvsW      -0.8060     0.1871    143      -4.31      <.0001  B11 Body Diff Gender Diff

                               Estimates
                                Standard
Label               Estimate       Error     DF    t Value    Pr > |t|
Actual Men            4.1795      0.2140    143      19.53      <.0001  B00
Actual Women          4.6567      0.2309    143      20.17      <.0001  B00+B10
Ideal Men             4.1795      0.1011    143      41.34      <.0001  B00+B01
Ideal Women           3.8507      0.1091    143      35.30      <.0001  B00+B01+B10+B11
MvsW for Actual       0.4772      0.3148    143       1.52      0.1317  B10
MvsW for Ideal       -0.3287      0.1487    143      -2.21      0.0287  B10+B11
AvsI for Men         -11E-14      0.1272    143      -0.00      1.0000  B01
AvsI for Women       -0.8060      0.1372    143      -5.87      <.0001  B01+B11
AvsI Gender Diff     -0.8060      0.1871    143      -4.31      <.0001  B11
```

Model 4a Predicting Only Difference Ratings with <u>a General Intercept</u> and Same R Matrix by Gender:

$$\widehat{Diff_i} = \beta_0 + \beta_1(MvsW_i)$$

```
display as result "STATA Univariate GLM Predicting Predicting Diff by Itself"
display as result "STATA Using REML in MIXED with Residual Variance Same by Gender"
mixed rating c.MvsW if dvD==1,  /// Predict only diff
         || personid: , noconstant variance reml  ///
         dfmethod(residual) dftable(pvalue)
lincom  c._cons*1 + c.MvsW*0, small // AvsI for Men
lincom  c._cons*1 + c.MvsW*1, small // AvsI for Women
lincom              c.MvsW*1, small // AvsI Gender Diff

TITLE1 "SAS Univariate General Linear Model Predicting Diff by Itself";
TITLE2 "SAS Using REML in MIXED with Residual Variance Same by Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvD=1; * Predict only diff DV;
     MODEL rating = MvsW / SOLUTION DDFM=Residual NOTEST;
     ESTIMATE "AvsI for Men"    intercept 1 MvsW 0;
     ESTIMATE "AvsI for Women"  intercept 1 MvsW 1;
     ESTIMATE "AvsI for Gender Diff"        MvsW 1;
RUN; TITLE2;
```

SAS Output for Model 4a—its prediction of difference scores is equivalent to Model 1a and Model 2a:

```
            Covariance Parameter Estimates
                         Standard         Z
Cov Parm      Estimate      Error     Value      Pr > Z
Residual        1.2621     0.1493      8.46      <.0001

           Fit Statistics
-2 Res Log Likelihood          447.67
AIC (Smaller is Better)        449.7
AICC (Smaller is Better)       449.7
BIC (Smaller is Better)        452.6
```

Model 4a only predicts difference scores as a single outcome, but its prediction is the same as in the previous models 1a, 2a, and 3a.

```
                   Solution for Fixed Effects
                         Standard
Effect        Estimate      Error     DF    t Value    Pr > |t|
Intercept            0     0.1272    143       0.00      1.0000  B0 Body Diff intercept
MvsW           -0.8060     0.1871    143      -4.31      <.0001  B1 Body Diff Gender Diff
```

```
                              Estimates
                                Standard
Label                  Estimate      Error      DF    t Value    Pr > |t|
AvsI for Men                  0     0.1272     143       0.00      1.0000   B0
AvsI for Women          -0.8060     0.1372     143      -5.87      <.0001   B0+B1
AvsI for Gender Diff    -0.8060     0.1871     143      -4.31      <.0001   B1
```

Model 4b Testing Different Residual Variance by Gender (btw, in SAS MIXED this can be used for any person predictor, although I am not sure how to do so in STATA MIXED):

```
display as result "STATA Using REML in MIXED with Residual Variance Separate by Gender"
mixed rating c.MvsW if dvD==1,  /// Predict only diff
          || personid: , noconstant variance reml residuals(independent,by(MvsW)) ///
          dfmethod(satterthwaite) dftable(pvalue) // by: R matrix separate by gender now

TITLE2 "SAS Using REML in MIXED Testing Residual Variance Separate by Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvD=1;     * Predict only diff DV;
     CLASS PersonID; * Need CLASS for REPEATED statement;
     MODEL rating = MvsW / SOLUTION DDFM=Satterthwaite NOTEST;
     * Put gender into log-linear model predicting residual variance amount;
     REPEATED / TYPE=VC LOCAL=EXP(MvsW) SUBJECT=PersonID;
RUN; TITLE1; TITLE2;
```

SAS Output for Model 4b adding prediction of log of residual variance: $Log\left(\sigma_{e_i}^2\right) = \upsilon_0 + \upsilon_1(MvsW_i)$

```
             Covariance Parameter Estimates
                             Standard          Z
Cov Parm       Estimate         Error      Value        Pr Z
EXP MvsW        -0.1532        0.2372      -0.65      0.5183 Difference in log(variance) between men and women
Residual         1.3507        0.2177       6.20      <.0001 Log(variance) for men (as reference)

           Fit Statistics
-2 Res Log Likelihood           447.25
AIC (Smaller is Better)         451.2
AICC (Smaller is Better)        451.3
BIC (Smaller is Better)         457.2
```

Does Model 4b with separate residual variance by gender fit better than Model 4a with the same residual variance across men and women?

$-2\Delta LL$ (3) = 447.67 – 447.25 = 0.42, p = .519, so diff res var is not better

```
  Null Model Likelihood Ratio Test
    DF     Chi-Square      Pr > ChiSq
     1           0.42          0.5193 → This is the LRT against model 4a in this case
```

One advantage of predicting a difference score directly is the ability to see how either of its component parts (actual in 5a or ideal in 5b) predicts the difference, and whether that prediction varies by gender. But both cannot predictors at the same time, given that one variable is a linear combination of the other two.

Model 5a Predicting Difference Ratings from Gender and Actual Rating (centered at 4):

$$\widehat{Diff}_i = \beta_0 + \beta_1(MvsW_i) + \beta_2(Actual_i - 4) + \beta_2(Actual_i - 4)(MvsW_i)$$

```
display as result "STATA Univariate GLM Predicting Predicting Diff from Actual and Gender"
display as result "STATA Using REML in MIXED with Residual Variance Same by Gender"
mixed rating c.MvsW c.Actual4 c.MvsW#c.Actual4 if dvD==1,  /// Predict only diff
          || personid: , noconstant variance reml  ///
          dfmethod(residual) dftable(pvalue)
lincom  c.Actual4*1 + c.MvsW#c.Actual4*0, small // Actual Predicts AvsI for Men
lincom  c.Actual4*1 + c.MvsW#c.Actual4*1, small // Actual Predicts AvsI for Women
lincom                c.MvsW#c.Actual4*1, small // Actual Predicts AvsI Gender Diff
```

```
TITLE1 "SAS Univariate GLM Predicting Diff From Actual and Gender";
TITLE2 "SAS Using REML in MIXED with Residual Variance Same By Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvD=1;  * Predict only diff DV;
     MODEL rating = MvsW Actual4 MvsW*Actual4 / SOLUTION DDFM=Residual NOTEST;
     ESTIMATE "Actual Predicts AvsI for Men"     Actual4 1 MvsW*Actual4 0;
     ESTIMATE "Actual Predicts AvsI for Women"   Actual4 1 MvsW*Actual4 1;
     ESTIMATE "Actual Predicts AvsI Gender Diff"           MvsW*Actual4 1;
RUN; TITLE1; TITLE2;
```

SAS Output for Model 5a:

Covariance Parameter Estimates

Cov Parm	Estimate	Standard Error	Z Value	Pr > Z
Residual	0.1234	0.01470	8.40	<.0001

Fit Statistics

-2 Res Log Likelihood	124.7
AIC (Smaller is Better)	126.7
AICC (Smaller is Better)	126.8
BIC (Smaller is Better)	129.7

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|	
Intercept	0.1026	0.03995	141	2.57	0.0113	B0 Body diff intercept
MvsW	-0.5426	0.06060	141	-8.95	<.0001	B1 Body diff gender dif at actual=4
Actual4	-0.5715	0.02086	141	-27.39	<.0001	B2 Body diff actual effect for men
MvsW*Actual4	0.01428	0.03128	141	0.46	0.6488	B2 Actual effect diff for women

Estimates

Label	Estimate	Standard Error	DF	t Value	Pr > |t|	
Actual Predicts AvsI for Men	-0.5715	0.02086	141	-27.39	<.0001	B2
Actual Predicts AvsI for Women	-0.5572	0.02331	141	-23.90	<.0001	B2+B3
Actual Predicts AvsI Gender Diff	0.01428	0.03128	141	0.46	0.6488	B3

Model 5b Predicting Difference Ratings from Gender and Ideal Rating (centered at 4):

$$\widehat{Diff_i} = \beta_0 + \beta_1(MvsW_i) + \beta_2(Ideal_i - 4) + \beta_2(Ideal_i - 4)(MvsW_i)$$

```
display as result "STATA Univariate GLM Predicting Predicting Diff from Ideal and Gender"
display as result "STATA Using REML in MIXED with Residual Variance Same by Gender"
mixed rating c.MvsW c.Ideal4 c.MvsW#c.Ideal4 if dvD==1,  /// Predict only diff
         || personid: , noconstant variance reml  ///
         dfmethod(residual) dftable(pvalue)
lincom  c.Ideal4*1 + c.MvsW#c.Ideal4*0, small // Ideal Predicts AvsI for Men
lincom  c.Ideal4*1 + c.MvsW#c.Ideal4*1, small // Ideal Predicts AvsI for Women
lincom              c.MvsW#c.Ideal4*1, small // Ideal Predicts AvsI Gender Diff
```

```
TITLE1 "SAS Univariate GLM Predicting Diff From Ideal and Gender";
TITLE2 "SAS Using REML in MIXED with VC R Matrix Same By Gender";
PROC MIXED DATA=work.Example5a NOCLPRINT COVTEST NAMELEN=100 METHOD=REML;
     WHERE dvD=1;  * Predict only diff DV;
     MODEL rating = MvsW Ideal4 MvsW*Ideal4 / SOLUTION DDFM=Residual NOTEST;
     ESTIMATE "Ideal Predicts AvsI for Men"     Ideal4 1 MvsW*Ideal4 0;
     ESTIMATE "Ideal Predicts AvsI for Women"   Ideal4 1 MvsW*Ideal4 1;
     ESTIMATE "Ideal Predicts AvsI Gender Diff"          MvsW*Ideal4 1;
RUN; TITLE1; TITLE2;
```

SAS Output for Model 5b:

```
            Covariance Parameter Estimates
                         Standard         Z
Cov Parm      Estimate      Error     Value      Pr > Z
Residual        0.5523    0.06578      8.40      <.0001

           Fit Statistics
-2 Res Log Likelihood          333.1
AIC (Smaller is Better)        335.1
AICC (Smaller is Better)       335.1
BIC (Smaller is Better)        338.0

                   Solution for Fixed Effects
                          Standard
Effect         Estimate      Error      DF    t Value    Pr > |t|
Intercept        0.1640    0.08580     141       1.91      0.0580  B0 Body diff intercept
MvsW            -1.1179     0.1259     141      -8.88      <.0001  B1 Body diff gender dif at actual=4
Ideal4          -0.9136    0.09327     141      -9.79      <.0001  B2 Body diff actual effect for men
MvsW*Ideal4    -0.07756     0.1401     141      -0.55      0.5808  B2 Actual effect diff for women

                                          Estimates
                                                 Standard
Label                              Estimate         Error      DF    t Value    Pr > |t|
Ideal Predicts AvsI for Men         -0.9136       0.09327     141      -9.79      <.0001  B2
Ideal Predicts AvsI for Women       -0.9911        0.1046     141      -9.48      <.0001  B2+B3
Ideal Predicts AvsI Gender Diff    -0.07756        0.1401     141      -0.55      0.5808  B3
```

Finally, let's examine the gender effect when body discrepancy as an ordinal outcome instead of interval:

Model 6 Predicting Differences by Gender using a Cumulative Logit Link and Multinomial Distribution:

$$Logit(Diff_{im} > -3 = \beta_{00} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -2 = \beta_{01} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -1 = \beta_{02} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -0 = \beta_{03} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -1 = \beta_{04} + \beta_1(MvsW_i)$$

Note this is a proportion odds model—the sample sizes are too small to test non-proportional odds (i.e., different gender effects per submodel).

```
display as result "STATA Univariate Generalized Linear Model Predicting Diff by Itself"
display as result "STATA Using ML in GLIMMIX Treating Difference as Ordinal"
gologit2 rating c.MvsW if dvD==1, pl     // Predict only diff using proportional odds
margins, at(c.MvsW=(0(1)1)) predict(xb) // logit of Diff>-3
margins, at(c.MvsW=(0(1)1))             // all probabilities
lincom c.MvsW, eform  // AvsI Gender Diff (and odds ratio)

TITLE1 "SAS Univariate Generalized Linear Model Predicting Diff by Itself";
TITLE2 "SAS Using ML in GLIMMIX Treating Difference as Ordinal";
PROC GLIMMIX DATA=work.Example5a NOCLPRINT NAMELEN=100 GRADIENT METHOD=MSPL;
     WHERE dvD=1; * Predict only diff DV;
     MODEL rating (DESCENDING) = MvsW / SOLUTION CHISQ LINK=CLOGIT DIST=MULT DDFM=NONE;
     ESTIMATE "AvsI Diff> 1 for Men"    intercept 1 0 0 0 0 MvsW 0 / ILINK;
     ESTIMATE "AvsI Diff> 0 for Men"    intercept 0 1 0 0 0 MvsW 0 / ILINK;
     ESTIMATE "AvsI Diff>-1 for Men"    intercept 0 0 1 0 0 MvsW 0 / ILINK;
     ESTIMATE "AvsI Diff>-2 for Men"    intercept 0 0 0 1 0 MvsW 0 / ILINK;
     ESTIMATE "AvsI Diff>-3 for Men"    intercept 0 0 0 0 1 MvsW 0 / ILINK;
     ESTIMATE "AvsI Diff> 1 for Women"  intercept 1 0 0 0 0 MvsW 1 / ILINK;
     ESTIMATE "AvsI Diff> 0 for Women"  intercept 0 1 0 0 0 MvsW 1 / ILINK;
     ESTIMATE "AvsI Diff>-1 for Women"  intercept 0 0 1 0 0 MvsW 1 / ILINK;
     ESTIMATE "AvsI Diff>-2 for Women"  intercept 0 0 0 1 0 MvsW 1 / ILINK;
     ESTIMATE "AvsI Diff>-3 for Women"  intercept 0 0 0 0 1 MvsW 1 / ILINK;
     ESTIMATE "AvsI Gender Diff"                             MvsW 1 / EXP;
RUN; TITLE1; TITLE2;
```

SAS Output for Model 6:

Fit Statistics	
-2 Log Likelihood	433.34
AIC (smaller is better)	445.34
AICC (smaller is better)	445.95
BIC (smaller is better)	463.20
CAIC (smaller is better)	469.20
HQIC (smaller is better)	452.60

Parameter Estimates

Effect	Body Rating Outcome	Estimate	Standard Error	DF	t Value	Pr > |t|	Gradient
Intercept	2	-2.7185	0.4285	Infty	-6.34	<.0001	-804E-14
Intercept	1	-0.5205	0.2274	Infty	-2.29	0.0221	-418E-15
Intercept	0	0.6772	0.2293	Infty	2.95	0.0031	-178E-13
Intercept	-1	2.5020	0.3095	Infty	8.08	<.0001	-218E-13
Intercept	-2	3.7421	0.4410	Infty	8.48	<.0001	4.65E-11
MvsW		-1.2633	0.3148	Infty	-4.01	<.0001	-217E-14

Estimates

Label	Estimate	Standard Error	DF	t Value	Pr > |t|	Mean	Standard Error Mean	Exponentiated Estimate
AvsI Diff> 1 for Men	-2.7185	0.4285	Infty	-6.34	<.0001	0.06189	0.02488	.
AvsI Diff> 0 for Men	-0.5205	0.2274	Infty	-2.29	0.0221	0.3727	0.05317	.
AvsI Diff>-1 for Men	0.6772	0.2293	Infty	2.95	0.0031	0.6631	0.05123	.
AvsI Diff>-2 for Men	2.5020	0.3095	Infty	8.08	<.0001	0.9243	0.02166	.
AvsI Diff>-3 for Men	3.7421	0.4410	Infty	8.48	<.0001	0.9768	0.009976	.
AvsI Diff> 1 for Women	-3.9818	0.4750	Infty	-8.38	<.0001	0.01831	0.008538	.
AvsI Diff> 0 for Women	-1.7838	0.2760	Infty	-6.46	<.0001	0.1438	0.03398	.
AvsI Diff>-1 for Women	-0.5862	0.2381	Infty	-2.46	0.0138	0.3575	0.05468	.
AvsI Diff>-2 for Women	1.2387	0.2680	Infty	4.62	<.0001	0.7753	0.04668	.
AvsI Diff>-3 for Women	2.4788	0.4045	Infty	6.13	<.0001	0.9226	0.02887	.
AvsI for Gender Diff	-1.2633	0.3148	Infty	-4.01	<.0001	Non-est	.	0.2827

Example results section for Part 1 Models non-redundant 1a, 1b, 5a, 5b, and 6:

The extent to which the difference between ideal body size and actual body size varied by gender was examined in 145 college students (*n*=78 men, *n*=67 women). Both body rating outcomes were measured on a scale of 1 to 9, with higher scores indicating larger bodies. The actual and ideal body ratings were first predicted in multivariate general linear models (i.e., using an identity link for each and a conditional multivariate normal distribution). The models were estimated using residual maximum likelihood and fixed effects were tested using Satterthwaite denominator degrees of freedom. ESTIMATE statements were used to estimate simple slopes and simple slope differences as linear combinations of the model fixed effects. All models allowed separate means and residual variances for the two outcomes, as well as a covariance among the residuals from the same person. Likelihood ratio tests revealed a nonsignificant improvement in model fit by allowing the residual variance–covariance matrix to differ by gender, and thus the residual variance–covariance matrix constrained equal across genders was used in the model reported below.

Table 1 provides the estimated means for each outcome by gender, all simple effects, and results of the interaction. There was a significant interaction between gender and body rating whose pattern can be understood as follows. Although men and women did not differ in their reported actual body (men = 4.180 vs. women = 4.657, p = .132), men thought their ideal body should be significantly heavier than women did (men = 4.180 vs. women = 3.851, p = .029). In addition, although men did not think they were different from their ideal on average (actual = 4.180 vs. ideal = 4.180, p = 1.00), women thought they were significantly heavier than their actual (actual = 4.657 vs. ideal = 3.851, p < .001). Women had a significantly larger body discrepancy than men (Diff = −0.806, p < .001).

We then predicted the body discrepancy difference scores directly in order to see if the gender difference held after controlling for the effect of actual or ideal body in predicting body discrepancy (and gender differences therein). Likelihood ratio tests again revealed a nonsignificant improvement in model fit by allowing the residual variance to differ by gender, and thus a residual variance constrained equal across genders was used in the models reported below.

In examining prediction of body discrepancy, the effect of actual body size was significantly negative in both men and women (equivalently so), which indicated that persons who reported larger actual bodies had more negative body discrepancies (i.e., they thought their ideal should be more smaller than persons who reported smaller actual bodies). The lack of significant interaction between gender and actual body size indicated that the gender difference in body discrepancy did not vary significantly as a function of actual body size. Parallel results were found for ideal body size. Finally, a univariate generalized linear model treating body discrepancy as ordinal (i.e., with a cumulative logit link and a multinomial conditional distribution) was estimated using maximum likelihood without denominator degrees of freedom. The negative effect of gender on body discrepancy remained significant, indicating that women thought their ideal body was more smaller than did men.

Part 2: Multivariate General and Generalized Linear Models via Path Analysis Software

In Part 2, we begin by estimating Model 3 using path analysis in Mplus and STATA SEM, whose software restrictions mean we must switch to maximum likelihood and test fixed effects without denominator degrees of freedom.

STATA Syntax to import wide-format data for path models:

```
// Import example 5a multivariate data and drop string gender
   use "$filesave\Example5aWide.dta", clear
   drop gender

// Example of how to export .csv file for use in Mplus
// Replace all missing values with -999 for Mplus
   mvencode _all, mv(-999)

// export delimited below: using lists the path and name of the new .csv file
// replace means it will be replaced if a file already exists with that name
// delimiter indicates a comma-delimited file
// nolabel will save actual data (numbers) instead of any value labels included
// novarnames tells it not to write the names to the top of the .csv file
   export delimited using "$filesave\Example5aWide1.csv", ///
                    delimiter(",") replace nolabel novarnames

// Re-import example 5a multivariate data (without missing value codes)
   use "$filesave\Example5aWide.dta", clear
   rename (mvsw) (MvsW) // Rename for consistency with SAS syntax
```

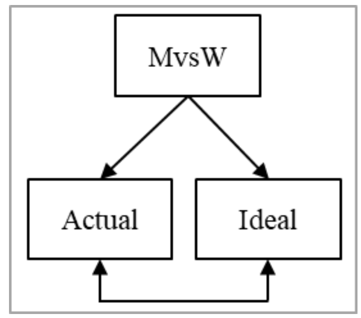
SAS Syntax to prepare wide-format data file in .csv format for Mplus:

```
* Export original wide format to Mplus;
DATA work.ForMplus; SET filesave.Example5aWide; DROP Gender;
     * Replace any missing values with -999;
     ARRAY vars(5) PersonID MvsW Actual Ideal Diff;
          DO i=1 TO 5; IF vars(i)=. THEN vars(i)=-999;
          END; DROP i; RUN;

PROC EXPORT DATA=work.ForMplus OUTFILE= "&filesave.\Example5aWide.csv"
     DBMS=CSV REPLACE; PUTNAMES=NO; RUN;
```

Model 1a Predicting Actual and Ideal Ratings with DV-Specific Intercepts and Same R Matrix by Gender:

$$\widehat{Rating}_{it} = \beta_{00}(Actual_{it}) + \beta_{01}(Ideal_{it}) + \beta_{10}(Actual_{it})(MvsW_i) + \beta_{11}(Ideal_{it})(MvsW_i)$$

STATA Syntax and Output for Previous Model 1a as a Path Model (estimated with ML; no denominator DF):




```
* /// means continue the command + comment
*  // means comment only

display as result "STATA Model 1a: Predicting Actual and Ideal with DV-Specific Intercepts"
sem                                       ///
   (actual ideal <- _cons)                /// All intercepts estimated (by default)
   (actual ideal <- mvsw),                /// Regressions: y outcomes ON x predictors
    var(e.actual e.ideal)                 /// Residual variances estimated (by default)
    covariance(e.actual*e.ideal)          /// Residual covariance (not by default)
    method(mlmv)                           // Full-information ML
    nlcom  _b[cov(e.actual,e.ideal):_cons] /                      ///
          (sqrt( _b[var(e.actual):_cons])*sqrt(_b[var(e.ideal):_cons])) // RCORR 2,1
    lincom _b[actual:_cons]                       // Actual for Men
    lincom _b[actual:_cons] + _b[actual:mvsw]     // Actual for Women
    lincom _b[ideal:_cons]                        // Ideal for Men
    lincom _b[ideal:_cons] + _b[ideal:mvsw]       // Ideal for Women
    lincom _b[actual:mvsw]                        // MvsW for Actual
    lincom _b[ideal:mvsw]                         // MvsW for Ideal
    lincom _b[ideal:_cons]  - _b[actual:_cons]    // AvsI for Men
    lincom _b[ideal:_cons]  + _b[ideal:mvsw] -    ///
           _b[actual:_cons] - _b[actual:mvsw]     // AvsI for Women
    lincom _b[ideal:mvsw]   - _b[actual:mvsw]     // AvsI Gender Diff
    sem, coeflegend                         // Print parameter labels
    sem, standardized                       // Print standardized solution
    estat gof, stats(all)                   // Print fit statistics
    estat eqgof                             // Print R2 per variable
```

```
Structural equation model                       Number of obs     =        145
Estimation method  = mlmv
Log likelihood     = -453.96021 → Does NOT match that of Mplus (even though fit tests do match)
--------------------------------------------------------------------------------------
                     |                 OIM
                     |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval] IN MIXED
---------------------+----------------------------------------------------------------
Structural           |   These unstandardized <- paths are the fixed slopes in MIXED.
  actual <-          |
                mvsw |   .4772292   .3125735     1.53   0.127    -.1354036    1.089862  B10 actual gender dif
               _cons |   4.179487   .2124739    19.67   0.000     3.763046    4.595928  B00 actual intercept
  -------------------+----------------------------------------------------------------
  ideal <-           |
                mvsw |  -.3287409   .1476922    -2.23   0.026    -.6182123   -.0392695  B11 ideal gender dif
               _cons |   4.179487   .1003947    41.63   0.000     3.982717    4.376257  B01 ideal intercept
---------------------+----------------------------------------------------------------
          Below are the residual variances and covariances from the R matrix in MIXED.
        var(e.actual)|   3.521322   .4135583                      2.797288     4.43276  UN(1,1)
         var(e.ideal)|   .7861699    .092331                      .6245222    .9896577  UN(2,2)
---------------------+----------------------------------------------------------------
cov(e.actual,e.ideal)|   1.531409   .1877925     8.15   0.000     1.163343    1.899476  UN(2,1)
--------------------------------------------------------------------------------------
LR test of model vs. saturated: chi2(0)    =      0.00, Prob > chi2 =      .

.     nlcom  _b[cov(e.actual,e.ideal):_cons] /                      ///
>          (sqrt( _b[var(e.actual):_cons])*sqrt(_b[var(e.ideal):_cons])) // RCORR 2,1
       _nl_1:  _b[cov(e.actual,e.ideal):_cons] / (sqrt(
_b[var(e.actual):_cons])*sqrt(_b[var(e.ideal):_cons]))
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .9204076   .0126935    72.51   0.000     .8955288    .9452864 RCORR 2,1
------------------------------------------------------------------------------

.     lincom  _b[actual:_cons]                       // Actual for Men
 ( 1)  [actual]_cons = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   4.179487   .2124739    19.67   0.000     3.763046    4.595928  B00
------------------------------------------------------------------------------

.         lincom  _b[actual:_cons] + _b[actual:mvsw]  // Actual for Women
 ( 1)  [actual]mvsw + [actual]_cons = 0
```

```
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   4.656716   .2292532    20.31   0.000     4.207388    5.106044  B00+B10
------------------------------------------------------------------------------
.     lincom  _b[ideal:_cons]                     // Ideal for Men
 ( 1)  [ideal]_cons = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   4.179487   .1003947    41.63   0.000     3.982717    4.376257  B10
------------------------------------------------------------------------------
.         lincom  _b[ideal:_cons] + _b[ideal:mvsw]    // Ideal for Women
 ( 1)  [ideal]mvsw + [ideal]_cons = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   3.850746    .108323    35.55   0.000     3.638437    4.063056  B01+B11
------------------------------------------------------------------------------
.     lincom _b[actual:mvsw]                      // MvsW for Actual
 ( 1)  [actual]mvsw = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   .4772292   .3125735     1.53   0.127    -.1354036    1.089862  B10
------------------------------------------------------------------------------
.     lincom _b[ideal:mvsw]                       // MvsW for Ideal
 ( 1)  [ideal]mvsw = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |  -.3287409   .1476922    -2.23   0.026    -.6182123   -.0392695  B11
------------------------------------------------------------------------------
.     lincom _b[ideal:_cons]  - _b[actual:_cons]  // AvsI for Men
 ( 1)  - [actual]_cons + [ideal]_cons = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |  -1.78e-15   .1263224    -0.00   1.000    -.2475874    .2475874  B01-B00
------------------------------------------------------------------------------
.     lincom _b[ideal:_cons]  + _b[ideal:mvsw] -  ///
>              _b[actual:_cons] - _b[actual:mvsw]   // AvsI for Women
 ( 1)  - [actual]mvsw - [actual]_cons + [ideal]mvsw + [ideal]_cons = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |  -.8059701   .1362982    -5.91   0.000     -1.07311   -.5388305  B01+B11-B00-B10
------------------------------------------------------------------------------
.     lincom _b[ideal:mvsw]   - _b[actual:mvsw]   // AvsI Gender Diff
 ( 1)  - [actual]mvsw + [ideal]mvsw = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |  -.8059701   .1858348    -4.34   0.000      -1.1702   -.4417407  B11-B10
------------------------------------------------------------------------------

.     sem, coeflegend                       // Print parameter labels, too (to use in lincom)
Structural equation model                       Number of obs     =        145
Estimation method  = mlmv
Log likelihood     = -453.96021
--------------------------------------------------------------------------------------
                     |      Coef.  Legend
---------------------+----------------------------------------------------------------
Structural           |
  actual <-          |
                mvsw |   .4772292  _b[actual:mvsw]
               _cons |   4.179487  _b[actual:_cons]
  -------------------+----------------------------------------------------------------
  ideal <-           |
                mvsw |  -.3287409  _b[ideal:mvsw]
               _cons |   4.179487  _b[ideal:_cons]
---------------------+----------------------------------------------------------------
        var(e.actual)|   3.521322  _b[var(e.actual):_cons]
         var(e.ideal)|   .7861699  _b[var(e.ideal):_cons]
---------------------+----------------------------------------------------------------
cov(e.actual,e.ideal)|   1.531409  _b[cov(e.actual,e.ideal):_cons]
--------------------------------------------------------------------------------------
```

This table from `sem,` **`coeflegend`** provides the parameter names for the LINCOM statements above.

```
.     sem, standardized                    // Print fully standardized solution, too

Structural equation model                       Number of obs     =        145
Estimation method  = mlmv
Log likelihood     = -453.96021
------------------------------------------------------------------------------------
                     |                 OIM
        Standardized |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
Structural           |
  actual <-          |
                mvsw |   .1257847   .0814076     1.55   0.122    -.0337713    .2853407
               _cons |   2.209566   .1815084    12.17   0.000     1.853816    2.565316
  -------------------+--------------------------------------------------------------
  ideal <-           |
                mvsw |  -.1817677   .0796357    -2.28   0.022    -.3378507   -.0256846
               _cons |   4.635207   .2756593    16.81   0.000     4.094925     5.17549
---------------------+--------------------------------------------------------------
        var(e.actual)|   .9841782   .0204797                      .9448463    1.025147
         var(e.ideal)|   .9669605   .0289504                      .9118516      1.0254
---------------------+--------------------------------------------------------------
cov(e.actual,e.ideal)|   .9204076   .0126935    72.51   0.000     .8955288    .9452864
------------------------------------------------------------------------------------
LR test of model vs. saturated: chi2(0)   =      0.00, Prob > chi2 =      .
```

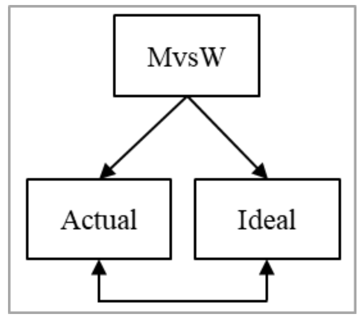
These standardized <- paths are standardized regression coefficients.

This standardized covariance is a residual correlation (in RCORR).

```
.     estat gof, stats(all)                // Print fit statistics
----------------------------------------------------------------------------
Fit statistic        |      Value   Description
---------------------+------------------------------------------------------
Likelihood ratio     |
          chi2_ms(0) |      0.000   model vs. saturated → Model is just-identified and fits perfectly
            p > chi2 |          .
          chi2_bs(3) |    279.538   baseline vs. saturated
            p > chi2 |      0.000
---------------------+------------------------------------------------------
Population error     |
               RMSEA |      0.000   Root mean squared error of approximation
 90% CI, lower bound |      0.000
         upper bound |      0.000
              pclose |      1.000   Probability RMSEA <= 0.05
---------------------+------------------------------------------------------
Information criteria |
                 AIC |    921.920   Akaike's information criterion            Does NOT match Mplus
                 BIC |    942.758   Bayesian information criterion            Does NOT match Mplus
---------------------+------------------------------------------------------
Baseline comparison  |
                 CFI |      1.000   Comparative fit index
                 TLI |      1.000   Tucker-Lewis index
---------------------+------------------------------------------------------
Size of residuals    |
                SRMR |      0.000   Standardized root mean squared residual
                  CD |      0.379   Coefficient of determination
----------------------------------------------------------------------------

.     estat eqgof                          // Print R2 per variable
Equation-level goodness of fit
------------------------------------------------------------------------------
             |          Variance           |
     depvars |    fitted  predicted   residual | R-squared        mc      mc2
-------------+-------------------------------+--------------------------------
observed     |                               |
      actual |  3.577931   .0566093   3.521322 |  .0158218  .1257847  .0158218
       ideal |  .8130321   .0268622   .7861699 |  .0330395  .1817677  .0330395
-------------+-------------------------------+--------------------------------
     overall |                               |  .3792589
------------------------------------------------------------------------------
mc  = correlation between depvar and its prediction
mc2 = mc^2 is the Bentler-Raykov squared multiple correlation coefficient
```

Mplus Syntax and Output for Previous Model 1a as a Path Model (estimated with ML; no denominator DF):

```
!!!!!!!!!!!!!!!!!!!!!!!!!!! Mplus Lines Cannot Exceed 90 Characters !!!!!!!!!!!!!!!!!!!!!
TITLE:  Mplus Model 1a: Predicting Actual and Ideal Ratings with DV-Specific Intercepts;
DATA:   FILE = Example5aWide.csv;  ! Can just list file name if in same folder;
        FORMAT = free;             ! FREE (default) or FIXED format;
        TYPE = individual;         ! Individual (default) or matrix data as input;
VARIABLE:
! List of ALL variables in original wide data file, in order;
! Mplus names must use 8 characters or fewer (so rename as needed);
  NAMES ARE PersonID MvsW Actual Ideal Diff;
! List of ALL variables used in model;
  USEVARIABLES ARE MvsW Actual Ideal;
! Missing data codes (here, -999);
  MISSING ARE ALL (-999);

ANALYSIS:    TYPE IS GENERAL;     ! Used for path models;
             ESTIMATOR IS ML;     ! Full-information maximum Likelihood;
OUTPUT:      CINTERVAL;           ! Print confidence intervals;
             STDYX;               ! Print fully standardized solution, too;

MODEL:  ! * --> Estimated parameter (labels to do math on);

! All residual variances estimated separately (by default);
  Actual* Ideal* (Aresvar Iresvar);
! Residual covariance (not estimated by default);
  Actual WITH Ideal* (AIrescov);
! All intercepts estimated separately (by default);
  [Actual* Ideal*] (Aint Iint);
! Regressions: y outcomes ON x predictors;
  Actual ON MvsW* (AonMvsW);    ! Gender diff for Actual;
  Ideal  ON MvsW* (IonMvsW);    ! Gender diff for Ideal;

! Get residual correlation, all means, simple effects, and interaction;
  MODEL CONSTRAINT:
  NEW (AIrescor A4M A4W I4M I4W MvsW4A MvsW4I AvsI4M AvsI4W AvsIMvsW);
  AIrescor = AIrescov / (SQRT(Aresvar)*SQRT(Iresvar)); ! RCORR 2,1
  A4M = Aint;                                 ! Actual for Men;
  A4W = Aint + AonMvsW;                       ! Actual for Women;
  I4M = Iint;                                 ! Ideal  for Men;
  I4W = Iint + IonMvsW;                       ! Ideal  for Women;
  MvsW4A = AonMvsW;                           ! MvsW for Actual;
  MvsW4I = IonMvsW;                           ! MvsW for Ideal;
  AvsI4M = Iint - Aint;                       ! AvsI for Men;
  AvsI4W = Iint + IonMvsW - Aint - AonMvsW;   ! AvsI for Women;
  AvsIMvsW = IonMvsW - AonMvsW;               ! AvsI Gender Diff;
```




```
THE MODEL ESTIMATION TERMINATED NORMALLY
MODEL FIT INFORMATION

Number of Free Parameters                        7   Total number of estimated parameters
Loglikelihood
          H0 Value                        -349.139   The model is just-identified so it fits perfectly.
          H1 Value                        -349.139
Information Criteria
          Akaike (AIC)                     712.278
          Bayesian (BIC)                   733.115
          Sample-Size Adjusted BIC         710.964
            (n* = (n + 2) / 24)
Chi-Square Test of Model Fit
          Value                              0.000
          Degrees of Freedom                     0
          P-Value                           0.0000
RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.000
          90 Percent C.I.                    0.000  0.000
          Probability RMSEA <= .05           0.000
CFI/TLI
          CFI                                1.000
          TLI                                1.000
Chi-Square Test of Model Fit for the Baseline Model
          Value                            279.538
          Degrees of Freedom                     3
          P-Value                           0.0000
SRMR (Standardized Root Mean Square Residual)
          Value                              0.000
```

```
MODEL RESULTS (UNSTANDARDIEZD SOLUTION; Mplus reorders them to list paths first)
                                                   Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value  IN MIXED
ACTUAL   ON
    MVSW               0.477      0.313      1.527      0.127  B10
IDEAL    ON
    MVSW              -0.329      0.148     -2.226      0.026  B11
ACTUAL   WITH
    IDEAL              1.531      0.188      8.155      0.000  UN(2,1)
Intercepts
    ACTUAL             4.179      0.212     19.671      0.000  B00
    IDEAL              4.179      0.100     41.631      0.000  B01
Residual Variances
    ACTUAL             3.521      0.414      8.515      0.000  UN(1,1)
    IDEAL              0.786      0.092      8.515      0.000  UN(2,2)
New/Additional Parameters (FROM MODEL CONSTRAINT)
    AIRESCOR           0.920      0.013     72.510      0.000  RCORR(2,1)
    A4M                4.179      0.212     19.671      0.000  B00
    A4W                4.657      0.229     20.313      0.000  B00+B10
    I4M                4.179      0.100     41.631      0.000  B01
    I4W                3.851      0.108     35.549      0.000  B01+B11
    MVSW4A             0.477      0.313      1.527      0.127  B10
    MVSW4I            -0.329      0.148     -2.226      0.026  B11
    AVSI4M             0.000      0.126      0.000      1.000  B01-B00
    AVSI4W            -0.806      0.136     -5.913      0.000  B01+B11-B00-B10
    AVSIMVSW          -0.806      0.186     -4.337      0.000  B11-B10
```

These unstandardized ON paths are the fixed slopes from MIXED.

This unstandardized WITH covariance is the residual covariance (2,1 in R).

Note that because we are using ML, the residual variances are smaller than in Part 1 MIXED (that used REML instead to avoid this downward bias).

```
STDYX Standardization - Standardized Solution
                                                   Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
 ACTUAL   ON
    MVSW               0.126      0.082      1.539      0.124
 IDEAL    ON
    MVSW              -0.182      0.080     -2.264      0.024
 ACTUAL   WITH
    IDEAL              0.920      0.013     72.510      0.000
 Intercepts
    ACTUAL             2.210      0.182     12.173      0.000
    IDEAL              4.635      0.276     16.806      0.000
 Residual Variances
    ACTUAL             0.984      0.021     47.866      0.000
    IDEAL              0.967      0.029     33.124      0.000
R-SQUARE
    Observed                                       Two-Tailed
    Variable        Estimate       S.E.  Est./S.E.    P-Value
    ACTUAL             0.016      0.021      0.769      0.442
    IDEAL              0.033      0.029      1.132      0.258
```

These standardized ON paths are standardized regression coefficients.

This standardized WITH covariance is a residual correlation (in RCORR).

Model 2a Predicting <u>Actual and Ideal Ratings</u> with a <u>General Intercept</u> and Same R Matrix by Gender:

$$\widehat{Rating}_{it} = \beta_{00} + \beta_{01}(Ideal_{it}) + \ \beta_{10}(MvsW_i) + \beta_{11}(Ideal_{it})(MvsW_i)$$

The path models below are equivalent to Model 2a with respect to the fixed effects in the model for the means, but not in the model for the variance (which has difference score residual variance in the path models instead of ideal).

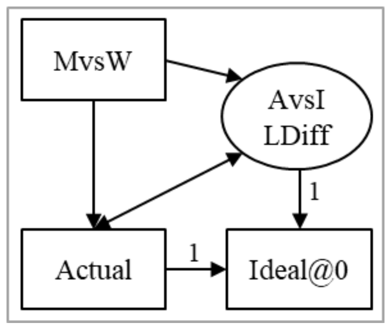
STATA Syntax for Analog to Previous Model 2a as a Path Model (estimated with ML; no denominator DF):

```
display as result "STATA Model 2a: Predicting Actual and Ideal with a General Intercept"
sem                                      ///
   (ideal@1 <- LDiff)                    /// Define "latent" difference variable IN CAPS
   (ideal <- actual@1)                   /// Creates the difference
   (actual LDiff ideal@0 <- _cons)       /// Shut off ideal intercept (move to LDiff)
   (actual LDiff <- mvsw),               /// Regressions: y outcomes ON x predictors
    var(e.actual e.LDiff e.ideal@0)      /// Shut off ideal residual variance (move to LDiff)
    covariance(e.actual*e.LDiff)         /// Residual covariance (not by default)
    method(mlmv)
    nlcom  _b[cov(e.actual,e.LDiff):_cons] /     ///
          (sqrt( _b[var(e.actual):_cons])*sqrt(_b[var(e.LDiff):_cons])) // RCORR 2,1
    lincom _b[actual:_cons]                   // Actual for Men
    lincom _b[actual:_cons] + _b[actual:mvsw] // Actual for Women
    lincom _b[actual:_cons] + _b[LDiff:_cons] // Ideal for Men
    lincom _b[actual:_cons] + _b[actual:mvsw] + ///
           _b[LDiff:_cons]    + _b[LDiff:mvsw] // Ideal for Women
    lincom _b[actual:mvsw]                    // MvsW for Actual
```

```
    lincom _b[actual:mvsw]  + _b[LDiff:mvsw]   // MvsW for Ideal
    lincom _b[LDiff:_cons]                     // AvsI for Men
    lincom _b[LDiff:_cons]  + _b[LDiff:mvsw]   // AvsI for Women
    lincom _b[LDiff:mvsw]                      // AvsI Gender Diff
```

Mplus Syntax and Output for Closest Analog to Previous Model 2a as a Path Model (estimated with ML; no denominator DF):

```
TITLE:   Mplus Model 2a: Predicting Actual and Ideal Ratings with a General Intercept;
DATA:    FILE = Example5aWide.csv;  ! Can just list file name if in same folder;
         FORMAT = free;             ! FREE (default) or FIXED format;
         TYPE = individual;         ! Individual (default) or matrix data as input;
VARIABLE:
! List of ALL variables in original wide data file, in order;
! Mplus names must use 8 characters or fewer (so rename as needed);
  NAMES ARE PersonID MvsW Actual Ideal Diff;
! List of ALL variables used in model;
  USEVARIABLES ARE MvsW Actual Diff;
! Missing data codes (here, -999);
  MISSING ARE ALL (-999);
ANALYSIS:    TYPE IS GENERAL;     ! Used for path models;
             ESTIMATOR IS ML;     ! Full-information maximum Likelihood;
OUTPUT:      CINTERVAL;           ! Print confidence intervals;
             STDYX;               ! Print fully standardized solution, too;

MODEL:  ! * --> Estimated parameter (labels to do math on);

! Create "latent" difference variable;
  LDiff BY Ideal@1;
  Ideal ON Actual@1; ! Creates the difference;

! Actual and LDiff residual variances estimated;
  Actual* LDiff* (Aresvar Dresvar);
  Ideal@0; ! Shut off ideal residual variance;

! Residual covariance (not estimated by default);
  Actual WITH LDiff* (ADrescov);

! Actual and LDiff intercepts estimated;
  [Actual* LDiff*] (Aint Dint);
  [Ideal@0]; ! Shut off ideal intercept;

! Regressions: y outcomes ON x predictors;
  Actual ON MvsW* (AonMvsW);    ! Gender diff for Actual;
  LDiff  ON MvsW* (DonMvsW);    ! Gender diff for AvsI;

! Get residual correlation, all means, simple effects, and interaction;
  MODEL CONSTRAINT:
  NEW (ADrescor A4M A4W I4M I4W AvsI4M AvsI4W AvsIMvsW);
  ADrescor = ADrescov / (SQRT(Aresvar)*SQRT(Dresvar)); ! RCORR 2,1
  A4M = Aint;                            ! Actual for Men;
  A4W = Aint + AonMvsW;                  ! Actual for Women;
  I4M = Aint + Dint;                     ! Ideal  for Men;
  I4W = Aint + AonMvsW + Dint + DonMvsW; ! Ideal  for Women;
  MvsW4A = AonMvsW;                      ! MvsW for Actual;
  MvsW4I = AonMvsW + DonMvsW;            ! MvsW for Ideal;
  AvsI4M = Dint;                         ! AvsI for Men;
  AvsI4W = Dint + DonMvsW;               ! AvsI for Women;
  AvsIMvsW = DonMvsW;                    ! AvsI Gender Diff;
```




```
UNSTANDARDIZED MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value   IN MIXED
LDIFF    BY
    IDEAL              1.000      0.000    999.000    999.000
 LDIFF    ON
    MVSW              -0.806      0.186     -4.337      0.000   B11
 IDEAL    ON
    ACTUAL             1.000      0.000    999.000    999.000
 ACTUAL   ON
    MVSW               0.477      0.313      1.527      0.127   B10
 ACTUAL   WITH
    LDIFF             -1.990      0.240     -8.296      0.000   not in mixed
 Intercepts
    ACTUAL             4.179      0.212     19.670      0.000   B00
    IDEAL              0.000      0.000    999.000    999.000
```

```
    LDIFF              0.000      0.126      0.000      1.000  B01
 Residual Variances
    ACTUAL             3.521      0.414      8.515      0.000  UN(1,1)
    IDEAL              0.000      0.000    999.000    999.000
    LDIFF              1.245      0.146      8.515      0.000  not in mixed
New/Additional Parameters
    ADRESCOR          -0.951      0.008   -118.552      0.000  RCORR(2,1)
    A4M                4.179      0.212     19.670      0.000  B00
    A4W                4.657      0.229     20.312      0.000  B00+B10
    I4M                4.179      0.100     41.630      0.000  B00+B01
    I4W                3.851      0.108     35.549      0.000  B00+B01+B10+B11
    MVSW4A             0.477      0.313      1.527      0.127  B10
    MVSW4I            -0.329      0.148     -2.226      0.026  B10+B11
    AVSI4M             0.000      0.126      0.000      1.000  B01
    AVSI4W            -0.806      0.136     -5.913      0.000  B01+B11
    AVSIMVSW          -0.806      0.186     -4.337      0.000  B11
```

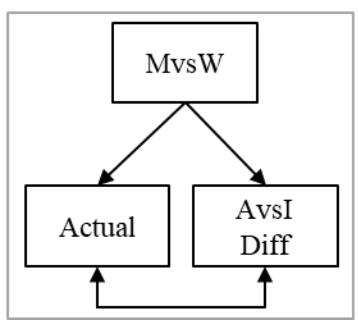
Model 3a Predicting Actual and Difference Ratings with <u>DV-Specific Intercepts</u> and Same R Matrix by Gender:

$$\widehat{Rating}_{it} = \beta_{00}(Actual_{it}) + \beta_{01}(Diff_{it}) + \beta_{10}(Actual_{it})(MvsW_i) + \beta_{11}(Diff_{it})(MvsW_i)$$

STATA Syntax for Previous Model 3a as a Path Model (estimated with ML; no denominator DF):

```
display as result "STATA Model 3a: Predicting Actual and Diff with DV-Specific Intercepts"
sem                                     ///
   (actual diff <- _cons)               /// All intercepts estimated (by default)
   (actual diff <- mvsw),               /// Regressions: y outcomes ON x predictors
    var(e.actual e.diff)                /// Residual variances estimated (by default)
    covariance(e.actual*e.diff)         /// Residual covariance (not by default)
    method(mlmv)                         // Full-information ML
    nlcom  _b[cov(e.actual,e.diff):_cons] /                        ///
          (sqrt( _b[var(e.actual):_cons])*sqrt(_b[var(e.diff):_cons])) // RCORR 2,1
    lincom _b[actual:_cons]                     // Actual for Men
    lincom _b[actual:_cons] + _b[actual:mvsw]   // Actual for Women
    lincom _b[actual:_cons] + _b[diff:_cons]    // Ideal for Men
    lincom _b[actual:_cons] + _b[actual:mvsw] + ///
           _b[diff:_cons]   + _b[diff:mvsw]     // Ideal for Women
    lincom _b[actual:mvsw]                      // MvsW for Actual
    lincom _b[actual:mvsw]  + _b[diff:mvsw]     // MvsW for Ideal
    lincom _b[diff:_cons]                       // AvsI for Men
    lincom _b[diff:_cons]   + _b[diff:mvsw]     // AvsI for Women
    lincom _b[diff:mvsw]                        // AvsI Gender Diff
```

Mplus Syntax and Output for Previous Model 3a as a Path Model (estimated with ML; no denominator DF):




```
TITLE:   Mplus Model 3a: Predicting Actual and Diff Ratings with DV-Specific Intercepts;
DATA:    FILE = Example5aWide.csv;  ! Can just list file name if in same folder;
         FORMAT = free;             ! FREE (default) or FIXED format;
         TYPE = individual;         ! Individual (default) or matrix data as input;
VARIABLE:
! List of ALL variables in original wide data file, in order;
! Mplus names must use 8 characters or fewer (so rename as needed);
  NAMES ARE PersonID MvsW Actual Ideal Diff;
! List of ALL variables used in model;
  USEVARIABLES ARE MvsW Actual Diff;
! Missing data codes (here, -999);
  MISSING ARE ALL (-999);
ANALYSIS:    TYPE IS GENERAL;     ! Used for path models;
             ESTIMATOR IS ML;     ! Full-information maximum likelihood;
OUTPUT:      CINTERVAL;           ! Print confidence intervals;
             STDYX;               ! Print fully standardized solution, too;
MODEL:  ! * --> Estimated parameter (labels to do math on);

! All residual variances estimated separately (by default);
  Actual* Diff* (Aresvar Dresvar);
! Residual covariance (not estimated by default);
  Actual WITH Diff* (ADrescov);
! All intercepts estimated separately (by default);
  [Actual* Diff*] (Aint Dint);

! Regressions: y outcomes ON x predictors;
  Actual ON MvsW* (AonMvsW);   ! Gender diff for Actual;
  Diff   ON MvsW* (DonMvsW);   ! Gender diff for AvsI;
```

```
! Get residual correlation, all means, simple effects, and interaction;
  MODEL CONSTRAINT:
  NEW (ADrescor A4M A4W I4M I4W AvsI4M AvsI4W AvsIMvsW);
  ADrescor = ADrescov / (SQRT(Aresvar)*SQRT(Dresvar)); ! RCORR 2,1
  A4M = Aint;                           ! Actual for Men;
  A4W = Aint + AonMvsW;                 ! Actual for Women;
  I4M = Aint + Dint;                    ! Ideal  for Men;
  I4W = Aint + AonMvsW + Dint + DonMvsW;    ! Ideal  for Women;
  MvsW4A = AonMvsW;                     ! MvsW for Actual;
  MvsW4I = AonMvsW + DonMvsW;           ! MvsW for Ideal;
  AvsI4M = Dint;                        ! AvsI for Men;
  AvsI4W = Dint + DonMvsW;              ! AvsI for Women;
  AvsIMvsW = DonMvsW;                   ! AvsI Gender Diff;
```

```
UNSTANDARDIZED MODEL RESULTS
                                                   Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value  IN MIXED
ACTUAL   ON
    MVSW               0.477      0.313      1.527      0.127  B10
DIFF     ON
    MVSW              -0.806      0.186     -4.337      0.000  B11
ACTUAL   WITH
    DIFF              -1.990      0.240     -8.296      0.000  UN(2,1)
Intercepts
    ACTUAL             4.179      0.212     19.671      0.000  B0
    DIFF               0.000      0.126      0.000      1.000  B01
Residual Variances
    ACTUAL             3.521      0.414      8.515      0.000  UN(1,1)
    DIFF               1.245      0.146      8.515      0.000  UN(2,2)
New/Additional Parameters from MODEL CONSTRAINT
    ADRESCOR          -0.951      0.008   -118.553      0.000  RCORR(2,1)
    A4M                4.179      0.212     19.671      0.000  B00
    A4W                4.657      0.229     20.313      0.000  B00+B10
    I4M                4.179      0.100     41.631      0.000  B00+B01
    I4W                3.851      0.108     35.549      0.000  B00+B01+B10+B11
    MVSW4A             0.477      0.313      1.527      0.127  B10
    MVSW4I            -0.329      0.148     -2.226      0.026  B10+B11
    AVSI4M             0.000      0.126      0.000      1.000  B01
    AVSI4W            -0.806      0.136     -5.913      0.000  B01+B11
    AVSIMVSW          -0.806      0.186     -4.337      0.000  B11
```

Model 5a Predicting Difference Ratings from Gender and Actual Rating (centered at 4):

$$\widehat{Diff_i} = \beta_0 + \beta_1(MvsW_i) + \beta_2(Actual_i - 4) + \beta_2(Actual_i - 4)(MvsW_i)$$

STATA Syntax for Previous Model 5a as a Path Model (estimated with ML; no denominator DF):

STATA v. 16 allows interactions to be defined within sem via # as usual (but I am using v. 14).

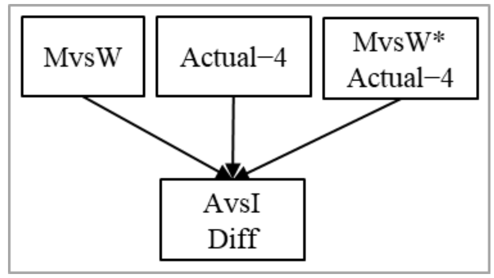
```
// Center predictor actual at 4
   gen actual4 = actual-4
// Create interaction variable
   gen mwxact4 = mvsw*actual4

display as result "STATA Model 5a: Predicting Diff Ratings from Actual and Gender"
sem                                     ///
   (diff <- _cons)                      /// Intercept estimated (by default)
   (diff <- mvsw actual4 mwxact4),      /// Regressions: y outcomes ON x predictors
    var(e.diff)                         /// Residual variance estimated (by default)
    method(mlmv)                         // Full-information ML
    lincom _b[diff:actual4]                     // Actual --> AvsI for Men
    lincom _b[diff:actual4] + _b[diff:mwxact4]  // Actual --> AvsI for Women
    lincom _b[diff:mwxact4]                     // Actual --> AvsI Gender Diff
```

Mplus Syntax and Output for Previous Model 5a as a Path Model (estimated with ML; no denominator DF):

```
TITLE:  Mplus Model 5a: Predicting Diff Ratings from Actual and Gender;
DATA:   FILE = Example5aWide.csv;  ! Can just list file name if in same folder;
        FORMAT = free;             ! FREE (default) or FIXED format;
        TYPE = individual;         ! Individual (default) or matrix data as input;

VARIABLE:
! List of ALL variables in original wide data file, in order;
! Mplus names must use 8 characters or fewer (so rename as needed);
  NAMES ARE PersonID MvsW Actual Ideal Diff;
```

```
! List of ALL variables used in model;
  USEVARIABLES ARE MvsW Diff;
! Missing data codes (here, -999);
  MISSING ARE ALL (-999);

DEFINE:     Actual4=Actual-4;      ! Center predictor Actual at 4;
            MWxAct4=MvsW*Actual4;  ! Create interaction term;

ANALYSIS:   TYPE IS GENERAL;     ! Used for path models;
            ESTIMATOR IS ML;     ! Full-information maximum likelihood;
OUTPUT:     CINTERVAL;           ! Print confidence intervals;
            STDYX;               ! Print fully standardized solution, too;
MODEL:  ! * --> Estimated parameter (labels to do math on);

! Residual variance estimated (by default);
  Diff* (Dresvar);
! Intercept estimated (by default);
  [Diff*] (Dint);
! Regressions: y outcomes ON x predictors;
  Diff   ON MvsW*      (DonMvsW);   ! Gender diff for AvsI;
  Diff   ON Actual4*   (DonAct4);   ! Actual4 --> AvsI;
  Diff   ON MWxAct4*   (DonMWA4);   ! Gender*Act4 --> AvsI;

! Get simple effects and interaction;
  MODEL CONSTRAINT:
  NEW (DActM DActW DActMW);
  DActM = DonAct4;               ! Actual4 --> AvsI for Men;
  DActW = DonAct4 + DonMWA4;     ! Actual4 --> AvsI for Women;
  DActMW = DonMWA4;              ! Actual4 --> AvsI Gender Diff;
```

DEFINE is used to create new variables (through math or functions). Interactions among observed variables must be created as new variables in Mplus.




```
UNSTANDARDIZED MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value   IN MIXED
DIFF     ON
    MVSW              -0.543      0.060     -9.080      0.000   B1
    ACTUAL4           -0.571      0.021    -27.777      0.000   B2
    MWXACT4            0.014      0.031      0.463      0.644   B3
Intercepts
    DIFF               0.103      0.039      2.603      0.009   B0
Residual Variances
    DIFF               0.120      0.014      8.515      0.000   RESIDUAL
New/Additional Parameters from MODEL CONSTRAINT
    DACTM             -0.571      0.021    -27.777      0.000   B2
    DACTW             -0.557      0.023    -24.240      0.000   B2+B3
    DACTMW             0.014      0.031      0.463      0.644   B3
```

Model 5b Predicting Difference Ratings from Gender and Ideal Rating (centered at 4):

$$\widehat{Diff}_i = \beta_0 + \beta_1(MvsW_i) + \beta_2(Ideal_i - 4) + \beta_2(Ideal_i - 4)(MvsW_i)$$

STATA Syntax for Previous Model 5b as a Path Model (estimated with ML; no denominator DF):

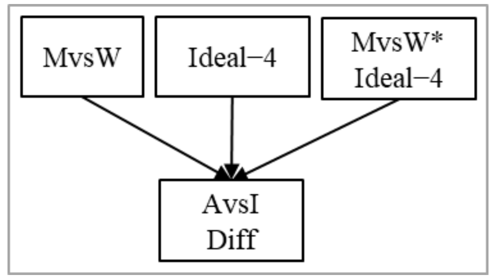
```
// Center predictor ideal at 4
   gen ideal4 = ideal-4
// Create interaction variable
   gen mwxid4 = mvsw*ideal4

display as result "STATA Model 5b: Predicting Diff Ratings from Ideal and Gender"
sem                                    ///
    (diff <- _cons)                    /// Intercept estimated (by default)
    (diff <- mvsw ideal4 mwxid4),      /// Regressions: y outcomes ON x predictors
     var(e.diff)                       /// Residual variance estimated (by default)
     method(mlmv)                       // Full-information ML
     lincom _b[diff:ideal4]                   // Ideal --> AvsI for Men
     lincom _b[diff:ideal4] + _b[diff:mwxid4] // Ideal --> AvsI for Women
     lincom _b[diff: mwxid4]                  // Ideal --> AvsI Gender Diff
```

Mplus Syntax and Output for Previous Model 5b as a Path Model (estimated with ML; no denominator DF):

```
TITLE:  Mplus Model 5b: Predicting Diff Ratings from Ideal and Gender;
DATA:   FILE = Example5aWide.csv;  ! Can just list file name if in same folder;
        FORMAT = free;             ! FREE (default) or FIXED format;
        TYPE = individual;         ! Individual (default) or matrix data as input;
```

```
VARIABLE:
! List of ALL variables in original wide data file, in order;
! Mplus names must use 8 characters or fewer (so rename as needed);
  NAMES ARE PersonID MvsW Actual Ideal Diff;
! List of ALL variables used in model;
  USEVARIABLES ARE MvsW Diff Ideal4 MWxAct4;
! Missing data codes (here, -999);
  MISSING ARE ALL (-999);
DEFINE:     Ideal4=Ideal-4;      ! Center predictor Ideal at 4;
            MWxId4=MvsW*Ideal4;  ! Create interaction term;
ANALYSIS:   TYPE IS GENERAL;     ! Used for path models;
            ESTIMATOR IS ML;     ! Full-information maximum likelihood;
OUTPUT:     CINTERVAL;           ! Print confidence intervals;
            STDYX;               ! Print fully standardized solution, too;
MODEL:  ! * --> Estimated parameter (labels to do math on);

! Residual variance estimated (by default);
  Diff* (Dresvar);
! Intercept estimated (by default);
  [Diff*] (Dint);
! Regressions: y outcomes ON x predictors;
  Diff   ON MvsW*     (DonMvsW);  ! Gender diff for AvsI;
  Diff   ON Ideal4*   (DonId4);   ! Ideal4 --> AvsI;
  Diff   ON MWxId4*   (DonMWI4);  ! Gender*Ideal4 --> AvsI;

! Get simple effects and interaction;
  MODEL CONSTRAINT:
  NEW (DIdM DIdW DIdMW);
  DIdM = DonId4;              ! Ideal4 --> AvsI for Men;
  DIdW = DonId4 + DonMWI4;    ! Ideal4 --> AvsI for Women;
  DIdMW = DonMWI4;            ! Ideal4 --> AvsI Gender Diff;
```

DEFINE is used to create new variables (through math or functions). Interactions among observed variables must be created as new variables in Mplus.




```
UNSTANDARDIZED MODEL RESULTS
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value   IN MIXED
DIFF     ON
    MVSW              -1.118      0.124     -9.005      0.000   B1
    IDEAL4            -0.913      0.092     -9.932      0.000   B2
    MWXID4            -0.078      0.138     -0.562      0.574   B3
Intercepts
    DIFF               0.164      0.085      1.937      0.053   B0
Residual Variances
    DIFF               0.537      0.063      8.515      0.000   RESIDUAL
New/Additional Parameters from MODEL CONSTRAINT
    DIDM              -0.913      0.092     -9.932      0.000   B2
    DIDW              -0.991      0.103     -9.612      0.000   B2+B3
    DIDMW             -0.078      0.138     -0.562      0.574   B3
```

Finally, let's examine the gender effect when body discrepancy as an ordinal outcome instead of interval:

Model 6 Predicting Differences by Gender using a Cumulative Logit Link and Multinomial Distribution:

$$Logit(Diff_{im} > -3 = \beta_{00} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -2 = \beta_{01} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -1 = \beta_{02} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -0 = \beta_{03} + \beta_1(MvsW_i)$$
$$Logit(Diff_{im} > -1 = \beta_{04} + \beta_1(MvsW_i)$$

Note this is a proportion odds model—the sample sizes are too small to test non-proportional odds (i.e., different gender effects per submodel).

STATA Syntax for Previous Model 6 as a Path Model (estimated with ML; no denominator DF):

```
display as result "STATA Model 6: Predicting Ordinal Diff Ratings from Gender"
gsem                                /// All thresholds estimated by default
    (diff <- mvsw, ologit),         /// Regressions: y outcomes ON x predictors
     coeflegend                      // Print parameter labels, too (to use in lincom)
     nlcom exp(_b[diff:mvsw])        // Odds ratio for AvsI gender diff
     // Can't figure out how to refer to thresholds in syntax :(
```

Mplus Syntax and Output for Model 6 as a Path Model (estimated with ML; no denominator DF):

```
TITLE:  Mplus Model 6: Predicting Ordinal Diff Ratings from Gender;
DATA:   FILE = Example5aWide.csv;  ! Can just list file name if in same folder;
        FORMAT = free;             ! FREE (default) or FIXED format;
        TYPE = individual;         ! Individual (default) or matrix data as input;
```

```
VARIABLE:
! List of ALL variables in original wide data file, in order;
! Mplus names must use 8 characters or fewer (so rename as needed);
  NAMES ARE PersonID MvsW Actual Ideal Diff;
! List of ALL variables used in model;
  USEVARIABLES ARE MvsW Diff Ideal4 MWxAct4;
! Missing data codes (here, -999);
  MISSING ARE ALL (-999);
! Treat Diff outcome as ordinal;
  CATEGORICAL IS Diff;
```

CATEGORICAL instructs Mplus to use a cumulative logit (default in ML) or probit link function and multinomial conditional distribution.

```
ANALYSIS:   TYPE IS GENERAL;     ! Used for path models;
            ESTIMATOR IS ML;     ! Full-information maximum likelihood;

OUTPUT:     CINTERVAL;           ! Print confidence intervals;
            STDYX;               ! Print fully standardized solution, too;

MODEL:  ! * --> Estimated parameter (labels to do math on);

! All thresholds estimated separately (by default);
  [Diff$1 Diff$2* Diff$3 Diff$4 Diff$5] (T1-T5);  ! In order of data

! Regressions: y outcomes ON x predictors
  Diff ON MvsW* (DonMvsW);    ! Gender diff for AvsI;

! Get odds ratio, illustrate predicted logits and probabilities;
  MODEL CONSTRAINT:
  NEW (ORMvsW LDp1M LDp1W PDp1M PDp1W);
  ORMvsW = EXP(DonMvsW);          ! Odds ratio for AvsI gender diff;
  LDp1M = -T5;                    ! Logit AvsI Diff>+1 for Men;
  LDp1W = -T5 + DonMvsW;          ! Logit AvsI Diff>+1 for Women;
  PDp1M = 1/(1+EXP(-1*LDp1M));    ! Probability AvsI Diff>+1 for Men;
  PDp1W = 1/(1+EXP(-1*LDp1W));    ! Probability AvsI Diff>+1 for Women;
```

```
MODEL FIT INFORMATION
Number of Free Parameters                        6
Loglikelihood
          H0 Value                        -216.669
Information Criteria
          Akaike (AIC)                     445.339
          Bayesian (BIC)                   463.199
          Sample-Size Adjusted BIC         444.213
            (n* = (n + 2) / 24)

MODEL RESULTS
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value   IN MIXED
 DIFF       ON
    MVSW              -1.263      0.315     -4.014      0.000   B1
 Thresholds
    DIFF$1            -3.742      0.441     -8.485      0.000   -B01
    DIFF$2            -2.502      0.310     -8.083      0.000   -B02
    DIFF$3            -0.677      0.229     -2.953      0.003   -B03
    DIFF$4             0.521      0.227      2.289      0.022   -B04
    DIFF$5             2.718      0.428      6.344      0.000   -B00
New/Additional Parameters from MODEL CONSTRAINT
    ORMVSW             0.283      0.089      3.177      0.001   EXP(B1)
    LDP1M             -2.718      0.428     -6.344      0.000   B04
    LDP1W             -3.982      0.475     -8.383      0.000   B04+B1
    PDP1M              0.062      0.025      2.488      0.013   1/(1+EXP(-1*(B04)))
    PDP1W              0.018      0.009      2.144      0.032   1/(1+EXP(-1*(B04+B1)))

RESULTS IN PROBABILITY SCALE (marginal across gender)
                    Estimate
 DIFF
    Category 1         0.048
    Category 2         0.096
    Category 3         0.334
    Category 4         0.255
    Category 5         0.225
    Category 6         0.042
```

Results Section for Part 2: see results from Part 1, as the models are the same!