Example 5: Multivariate General Linear Models for Family (Triadic) Data
Part 1 using Univariate Software: STATA MIXED, R GLS, and SAS MIXED
Part 2 using Path Analysis Software: Mplus, STATA SEM, and R LAVAAN
(complete syntax and output available for STATA, R, and SAS electronically)

These data were collected as part of a study of family dynamics conducted at Penn State University. The sample for this example includes 140 families with data from three family members (as three multivariate outcomes): a mother, a father, and an adult child. The example outcome is a scale mean (range from 1–4) of attitudes about gender roles in marriage, in which higher scores indicate more conservative attitudes. The example predictors are the gender of the adult child (0=girl, 1=boy) and the years of education of each family member (centered such that 0=12 years). In all models, we will use an unstructured **R** matrix (in which the residual variances and covariances are estimated separately for each outcome), although compound symmetry heterogeneous (with equal correlation across outcomes, but a separate variance for each outcome) or compound symmetry (equal covariance and equal variance across all outcomes) would be more parsimonious alternatives (if they fit not worse than unstructured via a likelihood ratio test).

We will predict all three family member outcomes simultaneously using two distinct analysis frameworks. In Part 1 we will estimate multivariate general linear models within univariate software (i.e., with an identity link and conditional multivariate normal distributions) using residual maximum likelihood (REML), and we will (try to) test fixed effects using Satterthwaite denominator degrees of freedom. In Part 2, we will estimate the same models using path analysis, (a truly multivariate modeling framework in which multiple columns can be predicted at once), whose software requires us to switch to maximum likelihood and to test fixed effects without denominator degrees of freedom. I am using manual dummy codes to distinguish the three outcomes rather than treating them as factor variables (i.e., letting the program create contrasts to do so), given that the latter option is not as readily available for path analysis.

The marginal outcome distributions of the showed some positive skew (with an observed floor effect for the adult children), but a conditional normal distribution appears to be a reasonable choice among the readily-available options for multivariate models. This is evidenced in the final model by predicted outcomes that stayed within the outcome bounds without the use a link function to do so, and plausible homogeneity of variance across predicted outcomes. In Part 2, we will also invoke robust standard errors that protect against deviations from residual multivariate normality.

Part 1 will require "reshaping" (i.e., stacking) our original data stored in <u>wide</u> (multivariate) format, in which one row holds all variables per family, with per-person versions in separate columns…

	FamilyID: Family ID Number	KidBoy: Kid's Gender (0=girl, 1=boy)	KidEd12: Kid's Years of Education (0=12)	MomEd12: Mother's Years of Edcation (0=12)	DadEd12: Father's Years of Edcation (0=12)	KidMarital: Kid's Marital Gender Attitudes Mean (1-4)	MomMarital: Mom's Marital Gender Attitudes Mean (1-4)	DadMarital: Dad's Marital Gender Attitudes Mean (1-4)
1	3996	1	2	2	2	1	1.8333333333	1
2	4425	1	3	0	0	1	1.3333333333	2.5

…into this new format called <u>long</u> (stacked, univariate), with one row per person per family:

	FamilyID: Family ID Number	KidBoy: Kid's Gender (0=girl, 1=boy)	KidEd12: Kid's Years of Education (0=12)	MomEd12: Mother's Years of Edcation	DadEd12: Father's Years of Edcation (0=12)	DV: 1K,2M,3D	kid: Is Adult Child (0=no, 1=yes)	mom: Is Mother (0=no, 1=yes)	dad: Is Father (0=no, 1=yes)	marital: Marital Gender Attitudes Mean (1-4)
1	3996	1	2	2	2	1.Kid	1	0	0	1
2	3996	1	2	2	2	2.Mom	0	1	0	1.83333333
3	3996	1	2	2	2	3.Dad	0	0	1	1
4	4425	1	3	0	0	1.Kid	1	0	0	1
5	4425	1	3	0	0	2.Mom	0	1	0	1.33333333
6	4425	1	3	0	0	3.Dad	0	0	1	2.5

Part 2 will use the original wide-format data for path analysis instead.

STATA Syntax for Importing and Stacking Wide Data into Long (to get one row per person per family):

```
// Defining global variable for file location to be replaced in code below
// \\Client\ precedes path in Virtual Desktop outside H drive;
global filesave "C:\Dropbox\24_PSQF6270\PSQF6270_Example5"

// Import Example 5a wide Stata data
use "$filesave\PSQF6270_Example5Wide.dta", clear

// Rename variables with numeric suffix to use with reshape (old)(new)
rename (kidmarital mommarital dadmarital) (marital1 marital2 marital3)

// Stack data: list multivariate variables first, i(higher index) j(repeated)
reshape long marital, i(familyid) j(DVnum)

// Create per-outcome dummy codes
gen kid=0
gen mom=0
gen dad=0
recode kid (0=1) if DVnum==1
recode mom (0=1) if DVnum==2
recode dad (0=1) if DVnum==3
// Label new variables
label variable DVnum   "DVnum: 1K,2M,3D"
label variable kid     "kid: Is Adult Child (0=no, 1=yes)"
label variable mom     "mom: Is Mother (0=no, 1=yes)"
label variable dad     "dad: Is Father (0=no, 1=yes)"
label variable marital "marital: Marital Gender Attitudes Mean (1-4)"
// Remove missing predictors or row-specific outcome (will happen anyway)
egen nummiss = rowmiss(kidboy kided12 momed12 daded12 marital)
drop if nummiss>0
```

R Syntax for Importing and Stacking Wide Data into Long (to get one row per person per family), after loading packages *haven*, *TeachingDemos*, *psych*, *multcomp*, *prediction*, *nlme*, and *lavaan*, as shown online:

```
# Define variables for working directory and data name
filesave = "C:\\Dropbox/24_PSQF6270/PSQF6270_Example5/"
filename = "PSQF6270_Example5Wide.sas7bdat"
setwd(dir=filesave)

# Import Example 5 SAS data
Example5_wide = read_sas(data_file=paste0(filesave,filename))
# Convert to data frame without labels to use for analysis
Example5_wide = as.data.frame(Example5_wide)

# Stack into long format (one row per outcome per family)
Example5 = reshape(Example5_wide, direction="long", idvar="FamilyID",
                   varying=c("KidMarital","MomMarital","DadMarital"),
                   v.names="marital", timevar="DVnum", times=c(1,2,3))

# Create per-person dummy codes
Example5$kid=0
Example5$mom=0
Example5$dad=0
Example5$kid[which(Example5$DVnum==1)]=1
Example5$mom[which(Example5$DVnum==2)]=1
Example5$dad[which(Example5$DVnum==3)]=1

# Remove missing predictors or row-specific outcome (will happen anyway)
Example5 = Example5[complete.cases(Example5[ ,
                    c("KidBoy","KidEd12","MomEd12","DadEd12","marital")]),]
```

Part 1: Multivariate General Linear Models via Univariate Software

Model 0a: Empty Means, Unstructured Variance Model Predicting Marital Conservative Gender Attitudes
General Intercept Version: $\widehat{Marital}_{fi} = \beta_{00} + \beta_{01}\left(Kid_{fi}\right) + \beta_{02}\left(Mom_{fi}\right)$

STATA Syntax and Partial Output for Model 0a:

```
display "STATA Empty Means, Unstructured Variance Models for Marital Attitudes"
display "STATA Model 0a: General Intercept (Dad=Ref DV) using 2 Dummy Codes"
mixed marital c.kid c.mom,        /// Fixed intercept will be for dad (as omitted DV)
      || familyid: , noconstant   /// This NOCONSTANT removes default family random intercept
      nolog reml residuals(unstructured,t(DVnum))       /// Unstructured R matrix by DV
      difficult dfmethod(satterthwaite) dftable(pvalue)  // Use Satterthwaite denominator DF
display "-2LL= " e(ll)*-2         // Print -2LL for model
lincom _cons*1  + c.kid*1, small  // Kid Intercept (Dad + diff)
lincom _cons*1  + c.mom*1, small  // Mom Intercept (Dad + diff)
lincom c.kid*-1 + c.mom*1, small  // Kid vs. Mom: Intercept Diff
```

```
Mixed-effects REML regression                   Number of obs     =        420
Group variable: familyid                        Number of groups  =        140
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
DF method: Satterthwaite                        DF:           min =     139.00
                                                              avg =     139.00
                                                              max =     139.00
                                                F(2,    139.00)   =      16.19 → Multiv Wald test given
Log restricted-likelihood = -353.47735          Prob > F          =     0.0000
------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
familyid:             (empty) | (No random effect variances in this model)
-----------------------------+------------------------------------------------
Residual: Unstructured       |
                     var(e1) |   .3311924   .0397272      .2618044    .4189707  Variance across Kids
                     var(e2) |   .3230136   .0387461      .2553391    .4086242  Variance across Moms
                     var(e3) |   .3195886   .0383353      .2526318    .4042916  Variance across Dads
                  cov(e1,e2) |    .041334    .027963     -.0134724    .0961405  Kid-Mom Covariance
                  cov(e1,e3) |   .0824049   .0284663       .026612    .1381978  Kid-Dad Covariance
                  cov(e2,e3) |   .0937145   .0283876      .0380758    .1493531  Mom-Dad Covariance
------------------------------------------------------------------------------
```

```
estat wcorrelation, covariance    // R matrix of variances and covariances across outcomes
estat wcorrelation                // RCORR matrix of correlations across outcomes
```

```
   Covariances for familyid = 3996:      Correlations:
          DV |       1        2       3            DV |       1        2        3
  -------------+-------------------------   -------------+-------------------------
           1 |  0.331                                1 |  1.000
           2 |  0.041    0.323                       2 |  0.126    1.000
           3 |  0.082    0.094    0.320              3 |  0.253    0.292    1.000
```

R and RCORR from estat wcorrelation

SDs for R also printed (not shown here)

R Syntax and Partial Output for Model 0a:

```
print("R Empty Means, Unstructured Variance Models for Marital Attitudes")
print("R Model 0a: General Intercept (Dad=Ref DV) using 2 Dummy Codes")
Model0a = gls(data=Example5, method="REML",
              model=marital~1+kid+mom,     # Fixed intercept will be for dad (as omitted)
              correlation=corSymm(form=~DVnum|FamilyID),  # Unstructured correlations
              weights=varIdent(form=~1|DVnum))            # Separate variance by DV
print("Print -2LL and Results
-2*logLik(Model0a); summary(Model0a)
```

```
'log Lik.' 706.95471 (df=9) → -2LL for model

Correlation Structure: General
  1     2
2 0.126
3 0.253 0.292
```

Inside of RCORR (given in full below)

```
Variance function:
 Structure: Different standard deviations per stratum
 Formula: ~1 | DV
 Parameter estimates:
     1.Kid       2.Mom       3.Dad
1.00000000 0.98757870 0.98232045
```

Weird multiplication factors to compute SD relative to first DV → ignore this

```
Residual standard error: 0.57549394
Degrees of freedom: 420 total; 417 residual
```

Naïve denominator DF given

```
print("Show R and RCORR matrices for first family in the data")
getVarCov(Model0a, individual="3996");  # R matrix = variances and covariances across outcomes
corMatrix(Model0a$modelStruct$corStruct)[[3]] # 3=rows/columns of R here, RCORR = correlations

Marginal variance covariance matrix
         [,1]     [,2]     [,3]
[1,] 0.331190 0.041336 0.082407
[2,] 0.041336 0.323020 0.093715
[3,] 0.082407 0.093715 0.319590
```

Actual **R** matrix!

```
> corMatrix(Model0a$modelStruct$corStruct)[[3]]
           [,1]       [,2]       [,3]
[1,] 1.00000000 0.12637845 0.25329512
[2,] 0.12637845 1.00000000 0.29167759
[3,] 0.25329512 0.29167759 1.00000000
```

Actual **RCORR** matrix!

```
print("DF=2 Intercept Diff -- Get error that it used Chi-Square instead of F")
F0a = glht(model=Model0a, linfct=rbind(c(0,1,0),c(0,0,1)), df=139)

Global Test:
   Chisq DF    Pr(>Chisq)
1 32.376  2 0.00000009324
```

R told me it wouldn't compute the F test… except it secretly did! So below I just asked for it

```
SaveF0a = summary(F0a, test=Ftest()); SaveF0a # Joint F-test
print("Get and show hidden results for F, dfnum, dfden, and p-value")
SaveF0a$test$fstat; SaveF0a$test$df; SaveF0a$df
[1,] 16.18809          [1] 2                [1] 139

pf(SaveF0a$test$fstat,df1=SaveF0a$test$df,df2=SaveF0a$df,lower.tail=FALSE)
[1,] 0.00000047859907

# model=marital~1+kid+mom
print("Missing Intercepts and Difference -- Had to give it correct Denominator DF")
summary(glht(model=Model0a, df=139, linfct=rbind(
  "Kid Intercept (Dad+Diff)"    = c(1,1,0),  # in order of fixed effects
  "Mom Intercept (Dad+Diff)"    = c(1,0,1),
  "Kid vs. Mom: Intercept Diff" = c(0,-1,1))), test=adjusted("none"))
```

Model 0a: $\widehat{Marital}_{fi} = \beta_{00} + \beta_{01}\left(Kid_{fi}\right) + \beta_{02}\left(Mom_{fi}\right)$

Model-Estimated Fixed Effects using General Intercept Version Model 0a from SAS:

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|	
Intercept	1.9560	0.04778	139	40.94	<.0001	Dad intercept B00
kid	-0.3264	0.05892	139	-5.54	<.0001	Kid intercept diff B01
mom	-0.05619	0.05702	139	-0.99	0.3261	Mom intercept diff B02

Requested Linear Combination Estimates using General Intercept Version Model 0a from SAS:

Estimates

Label	Estimate	Standard Error	DF	t Value	Pr > |t|	
Kid Intercept (Dad+diff)	1.6295	0.04864	139	33.50	<.0001	B00 + B01
Mom Intercept (Dad+diff)	1.8998	0.04803	139	39.55	<.0001	B00 + B02
Kid vs. Mom: Intercept Diff	0.2702	0.06389	139	4.23	<.0001	B02 - B01

Model 0b: Empty Means, Unstructured Variance Model for Marital Conservative Gender Attitudes
DV-Specific Intercept Version: $\widehat{Marital}_{fi} = \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi})$

STATA Syntax for Model 0b:

```
display "STATA Model 0b: DV-Specific Intercepts using All 3 Dummy Codes"
mixed marital c.kid c.mom c.dad, noconstant  /// This NOCONSTANT removes general fixed intercept
       || familyid: , noconstant             /// This NOCONSTANT removes family random intercept
      nolog reml residuals(unstructured,t(DVnum))       /// Unstructured R matrix by DV
      difficult dfmethod(satterthwaite) dftable(pvalue)  // Use Satterthwaite denominator DF
display "-2LL= " e(ll)*-2                   // Print -2LL for model
estat wcorrelation, covariance              // R matrix
estat wcorrelation                          // RCORR matrix
test (c.kid=c.mom)(c.kid=c.dad), small      // DF=2 Intercept Diff (small = use denominator DF)
lincom c.kid*-1 + c.mom*1, small            // Kid vs. Mom: Intercept Diff
lincom c.kid*-1 + c.dad*1, small            // Kid vs. Dad: Intercept Diff
lincom c.mom*-1 + c.dad*1, small            // Mom vs. Dad: Intercept Diff
```

R Syntax for Model 0b:

```
print("R Model 0b: DV-Specific Intercepts using All 3 Dummy Codes")
Model0b = gls(data=Example5, method="REML",
              model=marital~0+kid+mom+dad,                    # 0 removes fixed intercept
              correlation=corSymm(form=~DVnum|FamilyID),      # Unstructured correlations
              weights=varIdent(form=~1|DVnum))                # Separate variance by DV
print("Print -2LL and Results"); -2*logLik(Model0b); summary(Model0b)
print("Show R and RCORR matrices for first family in the data")
getVarCov(Model0b, individual="3996")  # R matrix = variances and covariances across outcomes
corMatrix(Model0b$modelStruct$corStruct)[[3]] # 3=rows/columns of R here, RCORR = correlations

print("DF=2 Intercept Diff -- Get error that it used Chi-Square instead of F")
F0c = glht(model=Model0b, linfct=rbind(c(-1,1,0),c(0,-1,1)), df=139)
SaveF0c = summary(F0c, test=Ftest()); SaveF0a # Joint F-test
print("Get and show hidden results for F, dfnum, dfden, and p-value")
SaveF0c$test$fstat; SaveF0c$test$df; SaveF0c$df
pf(SaveF0c$test$fstat,df1=SaveF0c$test$df,df2=SaveF0c$df,lower.tail=FALSE)

print("Pairwise Intercept Diffs -- Had to give it correct Denominator DF")
summary(glht(model=Model0b, df=139, linfct=rbind(
  "Kid vs. Mom: Intercept Diff" = c(-1,1,0),  # in order of fixed effects
  "Kid vs. Dad: Intercept Diff" = c(-1,0,1),
  "Mom vs. Dad: Intercept Diff" = c(0,-1,1))), test=adjusted("none"))
```

Model 0b: $\widehat{Marital}_{fi} = \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi})$

Model-Estimated Fixed Effects using DV-Specific Intercept Version from SAS:

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|	
kid	1.6295	0.04864	139	33.50	<.0001	Kid intercept B01
mom	1.8998	0.04803	139	39.55	<.0001	Mom intercept B02
dad	1.9560	0.04778	139	40.94	<.0001	Dad intercept B00

Requested Linear Combination Estimates using DV-Specific Intercept Version from SAS:

Estimates

Label	Estimate	Standard Error	DF	t Value	Pr > |t|	
Kid vs. Mom: Intercept Diff	0.2702	0.06389	139	4.23	<.0001	B02 - B01
Kid vs. Dad: Intercept Diff	0.3264	0.05892	139	5.54	<.0001	B00 - B01
Mom vs. Dad: Intercept Diff	0.05619	0.05702	139	0.99	0.3261	B00 - B02

To avoid confusion, we will proceed using Model 0b: DV-specific intercepts implemented via three dummy codes. This approach also aligns most directly with path model variants of these models (Part 2).

Model 1: DV-Specific Intercepts: To what extent does the kid's gender predict each persons' attitude?

$$\widehat{Marital}_{fi} = \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi})$$
$$+\beta_{10}(Dad_{fi})(KidBoy_f) + \beta_{11}(Kid_{fi})(KidBoy_f) + \beta_{12}(Mom_{fi})(KidBoy_f)$$

<u>STATA</u> Syntax for Model 1:

```
display "STATA Model 1: DV-Specific Intercepts -- Add Kid Gender"
mixed marital c.kid c.mom c.dad c.kid#c.kidboy c.mom#c.kidboy c.dad#c.kidboy, noconstant ///
      || familyid: , noconstant     /// This NOCONSTANT removes family random intercept
      nolog reml residuals(unstructured,t(DVnum))       /// Unstructured R matrix by DV
      difficult dfmethod(satterthwaite) dftable(pvalue)  // Use Satterthwaite denominator DF
display "-2LL= " e(ll)*-2           // Print -2LL for model
estat wcorrelation, covariance      // R matrix
estat wcorrelation                  // RCORR matrix

// DF=2 Diff in Kidboy Slope
test (c.kid#c.kidboy=c.mom#c.kidboy)(c.kid#c.kidboy=c.dad#c.kidboy), small
lincom c.kid#c.kidboy*-1 + c.mom#c.kidboy*1, small // Kid vs. Mom: Kidboy Slope Diff
lincom c.kid#c.kidboy*-1 + c.dad#c.kidboy*1, small // Kid vs. Dad: Kidboy Slope Diff
lincom c.mom#c.kidboy*-1 + c.dad#c.kidboy*1, small // Mom vs. Dad: Kidboy Slope Diff
lincom 0.5*(c.mom#c.kidboy*1 + c.dad#c.kidboy*1), small // Parent: Kidboy Slope
// Mom vs. Dad: Kidboy Slope Diff
lincom 0.5*(c.kid#c.kidboy*-2 + c.mom#c.kidboy*1 + c.dad#c.kidboy*1), small
```

<u>R</u> Syntax for Model 1:

```
print("R Model 1: DV-Specific Intercepts -- Add Kid Gender")
Model1 = gls(data=Example5, method="REML",
             model=marital~0+kid+mom+dad+kid:KidBoy+mom:KidBoy+dad:KidBoy,
             correlation=corSymm(form=~DVnum|FamilyID),  # Unstructured correlations
             weights=varIdent(form=~1|DVnum))            # Separate variance by DV
print("Print -2LL and Results"); -2*logLik(Model1); summary(Model1)

print("Show R and RCORR matrices for first family in the data")
getVarCov(Model1, individual="3996"); corMatrix(Model1$modelStruct$corStruct)[[3]]

print("DF=2 Diff in KidBoy Slope -- Get error that it used Chi-Square instead of F")
F1 = glht(model=Model1, linfct=rbind(c(0,0,0,-1,1,0),c(0,0,0,-1,0,1)), df=138)
SaveF1 = summary(F1, test=Ftest()); SaveF0a # Joint F-test
print("Get and show hidden results for F, dfnum, dfden, and p-value")
SaveF1$test$fstat; SaveF1$test$df; SaveF1$df
pf(SaveF1$test$fstat,df1=SaveF1$test$df,df2=SaveF1$df,lower.tail=FALSE)

print("KidBoy Slope Diffs -- Had to give it correct Denominator DF")
summary(glht(model=Model1, df=138, linfct=rbind(
  "Kid vs. Mom: KidBoy Slope Diff"     = c(0,0,0,-1,  1,  0),  # in order of fixed effects
  "Kid vs. Dad: KidBoy Slope Diff"     = c(0,0,0,-1,  0,  1),
  "Mom vs. Dad: KidBoy Slope Diff"     = c(0,0,0, 0, -1,  1),
  "Parent KidBoy Effect"               = c(0,0,0, 0,1/2,1/2),
  "Kids vs. Parent KidBoy Effect Diff" = c(0,0,0,-1,1/2,1/2))), test=adjusted("none"))
```

Partial SAS Output for Model 1: DV-Specific Intercepts adding Kid's Gender as Predictor for Each Attitude

Estimated R Matrix for FAMILYID 3996

Row	Col1	Col2	Col3
1	0.3136	0.03725	0.07733
2	0.03725	0.3244	0.09315
3	0.07733	0.09315	0.3203

Estimated R Correlation Matrix for FAMILYID 3996

Row	Col1	Col2	Col3
1	1.0000	0.1168	0.2440
2	0.1168	1.0000	0.2890
3	0.2440	0.2890	1.0000

Contrasts

Label	Num DF	Den DF	F Value	Pr > F
DF=2 Diff in KidBoy Slope?	2	138	1.90	0.1529

```
                    Solution for Fixed Effects
                           Standard
Effect         Estimate       Error      DF    t Value    Pr > |t|
kid              1.4950     0.06554     138      22.81      <.0001  Kid intercept B01
mom              1.8703     0.06666     138      28.06      <.0001  Mom intercept B02
dad              1.9178     0.06624     138      28.95      <.0001  Dad intercept B00
kid*KidBoy       0.2811     0.09474     138       2.97      0.0035  girl vs boy for Kid B11
mom*KidBoy      0.06152     0.09636     138       0.64      0.5242  girl vs boy for Mom B12
dad*KidBoy      0.07970     0.09575     138       0.83      0.4066  girl vs boy for Dad B10

                                        Estimates
                                                  Standard
Label                                 Estimate       Error      DF    t Value    Pr > |t|
Kid vs. Mom: KidBoy Slope Diff         -0.2196      0.1270     138      -1.73      0.0860  B12 - B11
Kid vs. Dad: KidBoy Slope Diff         -0.2014      0.1171     138      -1.72      0.0877  B10 - B11
Mom vs. Dad: KidBoy Slope Diff         0.01818      0.1145     138       0.16      0.8741  B10 - B12
Parent KidBoy Slope                    0.07061     0.07711     138       0.92      0.3614  0.5*(B10+B12)
Kid vs. Parents: KidBoy Slope Diff     -0.2105      0.1079     138      -1.95      0.0531  0.5*(B10+B12)-B11
```

It looks like we need to control for the effect of kid gender only for the kid (which makes sense, since we don't know about the gender of their siblings). Next, we'll test the effects of each person's education on their own attitude, followed by the incremental effect of dad's education on kid and mom attitudes after controlling for own education.

Model 2: DV-Specific Intercepts: To what extent does one's own education predict one's own attitude?

$$\widehat{Marital}_{fi} = \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi}) + \beta_{11}(Kid_{fi})(KidBoy_f)$$
$$+\beta_{20}(Dad_{fi})(DadEd_f - 12) + \beta_{31}(Kid_{fi})(KidEd_f - 12) + \beta_{42}(Mom_{fi})(MomEd_f - 12)$$

STATA Syntax for Model 2:

```
display "STATA Model 2: DV-Specific Intercepts -- KidBoy on Kid Only, Add Own Education"
mixed marital c.kid c.mom c.dad c.kid#c.kidboy                          ///
      c.kid#c.kided12 c.mom#c.momed12 c.dad#c.daded12, noconstant   ///
      || familyid: , noconstant   /// This NOCONSTANT removes family random intercept
      nolog reml residuals(unstructured,t(DVnum))       /// Unstructured R matrix by DV
      difficult dfmethod(satterthwaite) dftable(pvalue)  // Use Satterthwaite denominator DF
display "-2LL= " e(ll)*-2            // Print -2LL for model
estat wcorrelation, covariance       // R matrix
estat wcorrelation                   // RCORR matrix
```

R Syntax for Model 2:

```
print("R Model 2: DV-Specific Intercepts -- KidBoy on Kid Only, Add Own Educ")
Model2 = gls(data=Example5, method="REML",
             model=marital~0+kid+mom+dad +kid:KidBoy +kid:KidEd12+mom:MomEd12+dad:DadEd12,
             correlation=corSymm(form=~DVnum|FamilyID),  # Unstructured correlations
             weights=varIdent(form=~1|DVnum))            # Separate variance by DV
print("Print -2LL and Results"); -2*logLik(Model2); summary(Model2)

print("Show R and RCORR matrices for first family in the data")
getVarCov(Model2, individual="3996");  corMatrix(Model2$modelStruct$corStruct)[[3]]
```

Partial SAS Output for Model 2:

```
   Estimated R Matrix for FAMILYID 3996          Estimated R Correlation Matrix for FAMILYID 3996
 Row        Col1        Col2        Col3          Row        Col1        Col2        Col3
   1      0.3156     0.03837     0.07669            1      1.0000      0.1207      0.2501
   2     0.03837      0.3205     0.08441            2      0.1207      1.0000      0.2732
   3     0.07669     0.08441      0.2979            3      0.2501      0.2732      1.0000
```

```
                          Solution for Fixed Effects
                            Standard
Effect          Estimate       Error      DF    t Value    Pr > |t|
kid               1.5117     0.09814     141      15.40      <.0001  Kid intercept B01
mom               1.9359     0.05976     142      32.39      <.0001  Mom intercept B02
dad               2.0700     0.05663     145      36.55      <.0001  Dad intercept B00
kid*KidBoy        0.2641     0.09204     137       2.87      0.0048  girl vs boy for Kid B11
kid*KidEd12     -0.00280     0.02344     138      -0.12      0.9052  Kid Ed for kid B31
mom*MomEd12     -0.01725     0.01711     142      -1.01      0.3150  Mom Ed for mom B42
dad*DadEd12     -0.05447     0.01570     143      -3.47      0.0007  Dad Ed for dad B20
```

Model 3: DV-Specific Intercepts: To what extent does dad's education also predict kid and mom attitudes?

$$\widehat{Marital}_{fi} = \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi}) + \beta_{11}(Kid_{fi})(KidBoy_f)$$
$$+\beta_{20}(Dad_{fi})(DadEd_f - 12) + \beta_{31}(Kid_{fi})(KidEd_f - 12) + \beta_{42}(Mom_{fi})(MomEd_f - 12)$$
$$+\beta_{21}(Kid_{fi})(DadEd_f - 12) + \beta_{22}(Mom_{fi})(DadEd_f - 12)$$

STATA Syntax for Model 3:

```
display "STATA Model 3: DV-Specific Intercepts -- Add Dad Educ (Control for Own Educ)"
mixed marital c.kid c.mom c.dad c.kid#c.kidboy c.kid#c.kided12 c.mom#c.momed12  ///
      c.dad#c.daded12 c.kid#c.daded12 c.mom#c.daded12, noconstant               ///
      || familyid: , noconstant   /// This NOCONSTANT removes family random intercept
      nolog reml residuals(unstructured,t(DVnum))       /// Unstructured R matrix by DV
      difficult dfmethod(satterthwaite) dftable(pvalue)  // Use Satterthwaite denominator DF
display "-2LL= " e(ll)*-2          // Print -2LL for model
estat wcorrelation, covariance     // R matrix
estat wcorrelation                 // RCORR matrix
lincom c.kid#c.daded12*-1 + c.mom#c.daded12*1, small // Kid vs. Mom: DadEd12 Slope Diff
lincom c.kid#c.daded12*-1 + c.dad#c.daded12*1, small // Kid vs. Dad: DadEd12 Slope Diff
lincom c.mom#c.daded12*-1 + c.dad#c.daded12*1, small // Mom vs. Dad: DadEd12 Slope Diff
predict Model3pred, xb          // Save yhat from fixed effects
predict Model3res, rstandard    // Save "standardized" residuals from fixed effects
hist Model3res                  // Histogram of residuals (for normality)
graph export "$filesave\STATA Model 3 Residual Histogram.png", replace
twoway (scatter Model3res Model3pred)  // Scatterplot by predicted (for constant variance)
graph export "$filesave\STATA Model 3 Residual Scatterplot.png", replace
```

R Syntax for Model 3:

```
print("R Model 3: DV-Specific Intercepts -- Add Dad Educ (Control for Own Educ)")
Model3 = gls(data=Example5, method="REML",
             model=marital~0+kid+mom+dad+ kid:KidBoy +kid:KidEd12+mom:MomEd12+dad:DadEd12
                           +kid:DadEd12+mom:DadEd12,
             correlation=corSymm(form=~DVnum|FamilyID),  # Unstructured correlations
             weights=varIdent(form=~1|DVnum))            # Separate variance by DV
print("Print -2LL and Results"); -2*logLik(Model3); summary(Model3)
print("Show R and RCORR matrices for first family in the data")
getVarCov(Model3, individual="3996"); corMatrix(Model3$modelStruct$corStruct)[[3]]

print("DadEd Slope Diffs -- Had to give it correct Denominator DF")
summary(glht(model=Model3, df=136, linfct=rbind(
  "Kid vs. Mom: DadEd12 Slope Diff" = c(0,0,0,0,0,0,0,-1,1),  # in order of fixed effects
  "Kid vs. Dad: DadEd12 Slope Diff" = c(0,0,0,0,0,0,1,-1,0),
  "Mom vs. Dad: DadEd12 Slope Diff" = c(0,0,0,0,0,0,1,0,-1))), test=adjusted("none"))

print("Save yhat from fixed effects and Pearson residuals")
Example5$Model3pred = predict(Model3, type="response")
Example5$Model3res = residuals(Model3, type="pearson")
print ("Histogram of Residuals for normality")
hist(x=Example5$Model3res, freq=FALSE, ylab="Density",xlab="Model 3 Residuals")
print ("Scatterplot of residuals by prediced for constant variance")
plot(x=Example5$Model3res, y=Example5$Model3pred,
     ylab="Residual",xlab="Model 3 Predicted Outcome")
```

Partial SAS Output for Model 3:

$$\widehat{Marital}_{fi} = \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi}) + \beta_{11}(Kid_{fi})(KidBoy_f)$$
$$+\beta_{20}(Dad_{fi})(DadEd_f - 12) + \beta_{31}(Kid_{fi})(KidEd_f - 12) + \beta_{42}(Mom_{fi})(MomEd_f - 12)$$
$$+\beta_{21}(Kid_{fi})(DadEd_f - 12) + \beta_{22}(Mom_{fi})(DadEd_f - 12)$$

```
  Estimated R Matrix for FAMILYID 3996        Estimated R Correlation Matrix for FAMILYID 3996
Row        Col1        Col2        Col3        Row        Col1        Col2        Col3
  1      0.3179     0.03856     0.07720          1      1.0000      0.1204      0.2508
  2     0.03856      0.3229     0.08514          2      0.1204      1.0000      0.2744
  3     0.07720     0.08514      0.2982          3      0.2508      0.2744      1.0000

                Solution for Fixed Effects
                       Standard
Effect        Estimate        Error      DF    t Value    Pr > |t|
kid             1.5123       0.1003     140      15.08      <.0001  Kid intercept B01
mom             1.9373      0.06305     138      30.73      <.0001  Mom intercept B02
dad             2.0707      0.05769     138      35.89      <.0001  Dad intercept B00
kid*KidBoy      0.2639      0.09258     136       2.85      0.0050  girl vs boy for Kid B11
kid*KidEd12   -0.00264      0.02458     136      -0.11      0.9147  Kid Ed for kid B31
mom*MomEd12   -0.01624      0.02068     137      -0.79      0.4338  Mom Ed for mom B42
dad*DadEd12   -0.05484      0.01654     138      -3.32      0.0012  Dad Ed for dad B20
kid*DadEd12   -0.00048      0.01791     138      -0.03      0.9787  Dad Ed for kid B21
mom*DadEd12   -0.00169      0.02069     141      -0.08      0.9349  Dad Ed for mom B22

                                        Estimates
                                                    Standard
Label                                 Estimate        Error      DF    t Value    Pr > |t|
Kid vs. Mom: DadEd12 Slope Diff       -0.00121      0.02601     162      -0.05      0.9629  B22 - B21
Kid vs. Dad: DadEd12 Slope Diff       -0.05436      0.02127     143      -2.56      0.0117  B20 - B21
Mom vs. Dad: DadEd12 Slope Diff       -0.05314      0.02335     154      -2.28      0.0242  B20 - B22
```

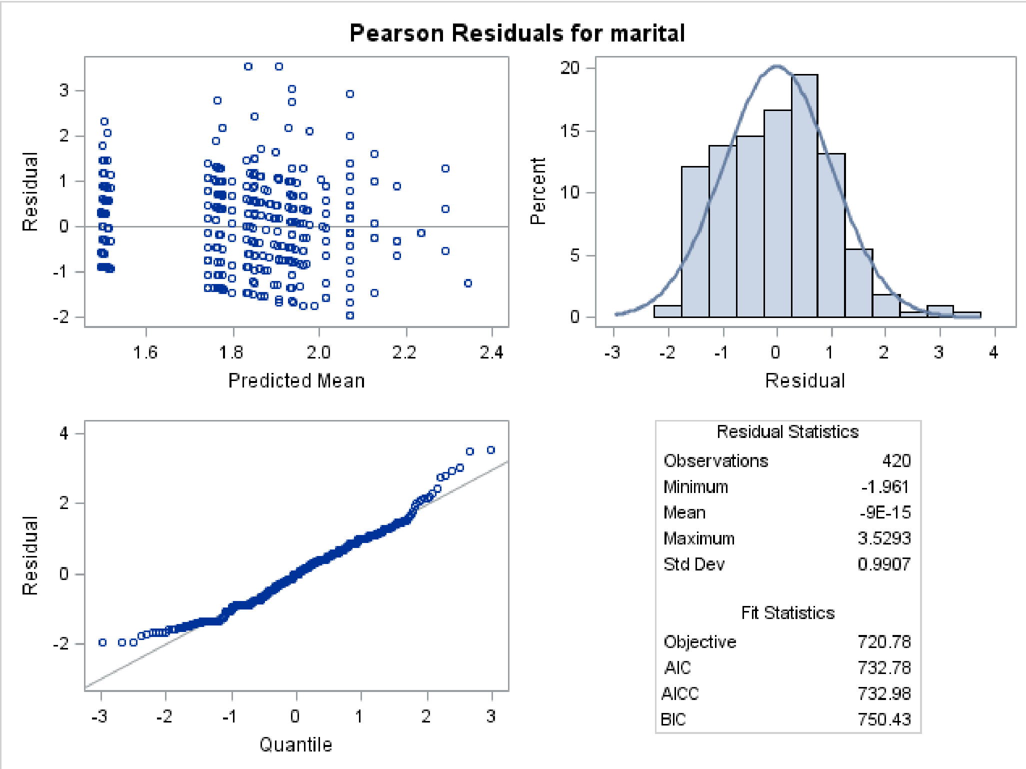
Moral of the story? Multivariate models can be estimated in univariate software to capture the relationships between person-specific predictors and person-specific outcomes (such as in "actor–partner" models for dyadic data as well).

Example results section [using SAS] for Part 1 Models 0–3:

The extent to which gender and education predicted marital attitudes was examined in 140 families, in which responses were collected from adult children, their mothers, and their fathers. Higher outcomes indicated more conservative marital attitudes (i.e., gender-traditional attitudes measured as the mean across items on a scale of 1 to 4). Given that the outcomes were correlated within families, multivariate general linear models (i.e., with conditionally multivariate normal residuals) were used to predict all three outcomes for each family simultaneously. All models were estimated using residual maximum likelihood and Satterthwaite denominator degrees of freedom. All models allowed separate means and residual variances across the three outcomes for the three types of family members, as well as covariances among the residuals from the same family. ESTIMATE statements were used to estimate simple slopes and simple slope differences as linear combinations of the model fixed effects. Prior to adding predictors, an empty means model (i.e., an unconditional model with no predictors) revealed significant differences in marital attitudes across type of family member, $F(2, 139) = 16.19$, $p < .001$. Although mean attitudes were similar across mothers and fathers (1.90 and 1.96, respectively, $p = .27$), the mean attitudes of children (1.63) were significantly less conservative on average than those of their parents ($p < .001$ for both comparisons).

To begin, we examined the extent to which the gender of the adult child (coded 0=woman, 1=man) who was surveyed was related to the martial attitudes of each type of family member. Although the attitudes of adult male children were significantly more conservative than those of adult female children (diff = 0.28, $p = .004$), there were no significant effects of the gender of the adult child for the marital attitudes of their mothers or fathers. Thus, we retained a predictor for the gender of the adult child only for the adult child's outcome. We then examined the extent to which the education (centered at 12 years) of each type of family member predicted their own attitudes, which was significant only for the father: for every additional year of father's education, his own attitudes were expected to be less conservative by 0.05 ($p < .001$). Next, we examined whether father's education incrementally predicted the marital attitudes of the mother or adult child after controlling for their own education, but neither effect was significant (and the effect of father's education on his own attitudes was significantly larger).

But how do we know if Model 3 is sufficient?? One aspect concerns the fit of the conditional distribution—in absence of Pearson χ^2/DF for normal residuals, we can examine residual plots, such as shown for SAS below:



These plots suggest some deviation from normality of the residuals, although the assumption of constant variance looks not terribly unreasonable.

Unfortunately, multivariate options for generalized linear models do not include beta-binomial alternatives that might have been useful here (given that the outcomes are bounded by 1 and 4). Also, given that all predicted outcomes stayed in bounds, it appears we don't necessarily need a link function.

Instead, we can see how the results differ using "robust" standard errors…so stay tuned for Part 2!

The other issue whether all relationships among the predictors and outcomes have been captured adequately by the model… for a more efficient way to answer that question, **stay tuned for Part 2 using path analysis**!

Part 2: Multivariate General Linear Models via Path Analysis Software

In Part 2, we begin by estimating Model 3 using path analysis in Mplus, STATA SEM, and R LAVAAN, which each require us to switch to maximum likelihood and test fixed effects without denominator degrees of freedom. For Model 4, we will also invoke "robust" standard errors (that correct for deviations from multivariate non-normality).

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

```
// Import Example 5 wide STATA data
use "$filesave\PSQF6270_Example5Wide.dta", clear

// Example of how to export a .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\PSQF6270_Example5Wide_STATA.csv", ///
                 delimiter(",") replace nolabel novarnames
```

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

```
# Example of how to export a .csv file for use in Mplus
# Copy data, replace all missing values with -999 for Mplus
Example5_Mplus = Example5_wide
Example5_Mplus[is.na(Example5_Mplus)] <- -999

# Write to .csv file without column names
write.table(x=Example5_Mplus, col.names=FALSE, row.names=FALSE, sep=",",
            file=paste0(filesave,"PSQF6270_Example5Wide_R.csv"))
```

Model 3: DV-Specific Intercepts: To what extent does dad's education also predict kid and mom attitudes?

$$\widehat{Marital}_{fi} = \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi}) + \beta_{11}(Kid_{fi})(KidBoy_f)$$
$$+\beta_{20}(Dad_{fi})(DadEd_f - 12) + \beta_{31}(Kid_{fi})(KidEd_f - 12) + \beta_{42}(Mom_{fi})(MomEd_f - 12)$$
$$+\beta_{21}(Kid_{fi})(DadEd_f - 12) + \beta_{22}(Mom_{fi})(DadEd_f - 12)$$

STATA Syntax and Output for Previous Model 3 as a Path Model (estimated with ML; regular SEs):

```
// Import Example 5 wide STATA data
use "$filesave\PSQF6270_Example5Wide.dta", clear

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

display "STATA Model 3: Own Education + Dad Education a Predictor of Each Attitude"
display "Using SEM to create path analysis model estimated with ML on wide-format data"
sem                                           ///
   (kidmarit mommarit dadmarit <- _cons)      /// All intercepts estimated (by default)
   (kidmarit <- kidboy kided12)               /// Regressions: y outcomes ON x predictors
   (mommarit <- momed12)                      ///
   (kidmarit mommarit dadmarit <- daded12),   ///
    var(e.kidmarit e.mommarit e.dadmarit)     /// All residual variances estimated (by default)
    covariance(e.kidmarit*e.mommarit          /// All pairwise residual covariances (not default)
               e.mommarit*e.dadmarit          ///
               e.kidmarit*e.dadmarit)         ///
    method(mlmv)                               // Full-information ML
    lincom _b[mommarital:daded12] - _b[kidmarital:daded12] // Kid v. Mom: Dad Educ Effect Diff
    lincom _b[dadmarital:daded12] - _b[kidmarital:daded12] // Kid v. Dad: Dad Educ Effect Diff
    lincom _b[dadmarital:daded12] - _b[mommarital:daded12] // Mom v. Dad: Dad Educ Effect Diff
    sem, coeflegend                        // Print parameter labels, too (to use in lincom)
```

```
sem, standardized                       // Print fully standardized solution, too
estat gof, stats(all)                   // Print fit statistics
display "LL for H1 Model= " e(critvalue_s)
display "# of parameters= " e(df_m)
display "-2LL= " e(ll)*-2               // Print -2LL for model
estat eqgof                             // Print R2 per variable
estat residuals                         // Print how far off each predicted covariance is
estat mindices, minchi2(3.84) showpclass(all) // Print cheat codes to improve model fit p<.05
```

```
Structural equation model                       Number of obs     =        140
Estimation method  = mlmv
Log likelihood     = -1374.4822 → Does NOT match Mplus because all predictors are in the likelihood,
                                  not just the outcomes, but rest of the fit tests do match
------------------------------------------------------------------------------------------------
UNSTANDARDIZED SOLUTION      |                 OIM
                             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]   IN MIXED
-----------------------------+------------------------------------------------------------------
Structural                   |
  kidmarital <-              |   These unstandardized <- paths are the fixed slopes in MIXED.
                      kidboy |   .2638938   .0914365     2.89   0.004     .0846816    .4431059    B11
                     kided12 |   -.002641   .0242338    -0.11   0.913    -.0501385    .0448565    B31
                     daded12 |  -.0004795   .0176566    -0.03   0.978    -.0350857    .0341268    B21
                       _cons |   1.512271   .0989087    15.29   0.000     1.318414    1.706129    B01
  ---------------------------+------------------------------------------------------------------
  mommarital <-              |
                     momed12 |  -.0162593   .0211854    -0.77   0.443    -.0577819    .0252634    B42
                     daded12 |  -.0016793   .0206962    -0.08   0.935    -.0422431    .0388845    B22
                       _cons |   1.937305    .062596    30.95   0.000     1.814619    2.059991    B02
  ---------------------------+------------------------------------------------------------------
  dadmarital <-              |
                     daded12 |  -.0548368    .016422    -3.34   0.001    -.0870233   -.0226502    B20
                       _cons |   2.070718   .0572756    36.15   0.000      1.95846    2.182976    B00
-----------------------------+------------------------------------------------------------------
        Below are the residual variances and covariances from the R matrix in MIXED.

           var(e.kidmarital)|   .3091381   .0369567                      .2445646    .3907613     UN(1,1)
           var(e.mommarital)|   .3161529   .0379111                      .2499347    .3999152     UN(2,2)
           var(e.dadmarital)|   .2938981   .0351275                      .2325192    .3714795     UN(3,3)
----------------------------+-------------------------------------------------------------------
cov(e.kidmarital,e.mommarital)|   .0380059   .0266924     1.42   0.154    -.0143102     .090322     UN(2,1)
cov(e.kidmarital,e.dadmarital)|   .0761007   .0263037     2.89   0.004     .0245463    .1276551     UN(3,1)
cov(e.mommarital,e.dadmarital)|   .0839167   .0273732     3.07   0.002     .0302662    .1375671     UN(3,2)
------------------------------------------------------------------------------------------------
LR test of model vs. saturated: chi2(6)   =     10.93, Prob > chi2 = 0.0906
```

```
.    lincom _b[mommarital:daded12] - _b[kidmarital:daded12] // Kid v. Mom: Dad Educ Effect Diff
 ( 1)  - [kidmarital]daded12 + [mommarital]daded12 = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |  -.0011998   .0258607    -0.05   0.963    -.0518858    .0494862   B22 - B21
------------------------------------------------------------------------------

.     lincom _b[dadmarital:daded12] - _b[kidmarital:daded12] // Kid v. Dad: Dad Educ Effect Diff
 ( 1)  - [kidmarital]daded12 + [dadmarital]daded12 = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |  -.0543573   .0210185    -2.59   0.010    -.0955527   -.0131618   B20 - B21
------------------------------------------------------------------------------

.     lincom _b[dadmarital:daded12] - _b[mommarital:daded12] // Mom v. Dad: Dad Educ Effect Diff
 ( 1)  - [mommarital]daded12 + [dadmarital]daded12 = 0
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |  -.0531575    .023324    -2.28   0.023    -.0988717   -.0074432   B20 - B22
------------------------------------------------------------------------------
```

```
.    sem, coeflegend                        // Print parameter labels, too (to use in lincom)
-----------------------------------------------------------------------------------------------
                              |      Coef.  Legend
------------------------------+----------------------------------------------------------------
Structural                    |
  kidmarital <-               |
                       kidboy |   .2638938  _b[kidmarital:kidboy]
                      kided12 |   -.002641  _b[kidmarital:kided12]
                      daded12 |  -.0004795  _b[kidmarital:daded12]
                        _cons |   1.512271  _b[kidmarital:_cons]
  ----------------------------+----------------------------------------------------------------
  mommarital <-               |
                      momed12 |  -.0162593  _b[mommarital:momed12]
                      daded12 |  -.0016793  _b[mommarital:daded12]
                        _cons |   1.937305  _b[mommarital:_cons]
  ----------------------------+----------------------------------------------------------------
  dadmarital <-               |
                      daded12 |  -.0548368  _b[dadmarital:daded12]
                        _cons |   2.070718  _b[dadmarital:_cons]
------------------------------+----------------------------------------------------------------
            var(e.kidmarital)|   .3091381  _b[var(e.kidmarital):_cons]
            var(e.mommarital)|   .3161529  _b[var(e.mommarital):_cons]
            var(e.dadmarital)|   .2938981  _b[var(e.dadmarital):_cons]
------------------------------+----------------------------------------------------------------
cov(e.kidmarital,e.mommarital)|   .0380059  _b[cov(e.kidmarital,e.mommarital):_cons]
cov(e.kidmarital,e.dadmarital)|   .0761007  _b[cov(e.kidmarital,e.dadmarital):_cons]
cov(e.mommarital,e.dadmarital)|   .0839167  _b[cov(e.mommarital,e.dadmarital):_cons]
-----------------------------------------------------------------------------------------------
LR test of model vs. saturated: chi2(6)   =     10.93, Prob > chi2 = 0.0906
```

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

```
.    sem, standardized                      // Print fully standardized solution, too
-----------------------------------------------------------------------------------------------
 Standardized Solution:       |                 OIM
 All variables M=0, SD=1      |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------+----------------------------------------------------------------
Structural                    |
  kidmarital <-               |
                       kidboy |   .2306503   .0770785     2.99   0.003     .0795792    .3817214
                      kided12 |  -.0090898   .0834042    -0.11   0.913    -.1725591    .1543794
                      daded12 |  -.0023406   .0861915    -0.03   0.978    -.1712728    .1665916
                        _cons |   2.645964   .2466043    10.73   0.000     2.162628    3.129299
  ----------------------------+----------------------------------------------------------------
  mommarital <-               |
                      momed12 |  -.0782303   .1019932    -0.77   0.443    -.2781333    .1216728
                      daded12 |  -.0083038   .1023122    -0.08   0.935     -.208832    .1922244
                        _cons |   3.433518   .2280257    15.06   0.000     2.986595     3.88044
  ----------------------------+----------------------------------------------------------------
  dadmarital <-               |
                      daded12 |  -.2716069   .0768234    -3.54   0.000     -.422178   -.1210357
                        _cons |   3.676054   .2200636    16.70   0.000     3.244738    4.107371
------------------------------+----------------------------------------------------------------
            var(e.kidmarital)|   .9463698   .0355442                         .8792068    1.018663
            var(e.mommarital)|   .9930701   .0139521                         .9660976    1.020796
            var(e.dadmarital)|   .9262297   .0417315                         .8479448    1.011742
------------------------------+----------------------------------------------------------------
cov(e.kidmarital,e.mommarital)|     .12157   .0835428     1.46   0.146    -.0421709    .2853109
cov(e.kidmarital,e.dadmarital)|   .2524724   .0792209     3.19   0.001     .0972022    .4077426
cov(e.mommarital,e.dadmarital)|   .2752969   .0801933     3.43   0.001     .1181209     .432473
-----------------------------------------------------------------------------------------------
```

These standardized <- paths are standardized regression coefficients.

These standardized covariances are residual correlations (in RCORR).

```
.    estat gof, stats(all)                          // Print fit statistics
----------------------------------------------------------------------------
Fit statistic        |      Value   Description (from STATA!)                 Notes from Lesa:
---------------------+------------------------------------------------------
Likelihood ratio     |
          chi2_ms(6) |     10.929   model vs. saturated                       -This is -2ΔLL for our H0-H1
            p > chi2 |      0.091                                              Test of exact fit: NS is good!
         chi2_bs(15) |     52.998   baseline vs. saturated                    -This is -2ΔLL for H0-H1 if
            p > chi2 |      0.000                                              H0 had no paths at all
---------------------+------------------------------------------------------
```

```
Population error     |
               RMSEA |      0.077   Root mean squared error of approximation  Should be < .08 or so
 90% CI, lower bound |      0.000
         upper bound |      0.148
              pclose |      0.229   Probability RMSEA <= 0.05                 Test of exact fit: NS is good!
---------------------+------------------------------------------------------
Information criteria |
                 AIC |   2778.964   Akaike's information criterion            Does not match Mplus
                 BIC |   2823.089   Bayesian information criterion            Does not match Mplus
---------------------+------------------------------------------------------
Baseline comparison  |
                 CFI |      0.870   Comparative fit index                     Should be > .9 or so
                 TLI |      0.676   Tucker-Lewis index                        Should be > .9 or so
---------------------+------------------------------------------------------
Size of residuals    |
                SRMR |      0.039   Standardized root mean squared residual   Should be < .05 or so
                  CD |      0.132   Coefficient of determination              Like an overall R2 across DVs
----------------------------------------------------------------------------
```

```
.    estat eqgof                          // Print R2 per variable
Equation-level goodness of fit
------------------------------------------------------------------------------
             |           Variance           |
     depvars |    fitted  predicted  residual | R-squared        mc      mc2
-------------+------------------------------+---------------------------------
observed     |                              |
  kidmarital |  .3266568   .0175187  .3091381 |  .0536302   .231582  .0536302
  mommarital |  .3183591   .0022062  .3161529 |  .0069299  .0832462  .0069299
  dadmarital |  .3173058   .0234077  .2938981 |  .0737703  .2716069  .0737703
-------------+------------------------------+---------------------------------
     overall |                              |  .1323532
------------------------------------------------------------------------------
mc  = correlation between depvar and its prediction
mc2 = mc^2 is the Bentler-Raykov squared multiple correlation coefficient
```

```
.    estat residuals                      // Print how far off each predicted covariance is
Residuals of observed variables
  Mean residuals
             | kidmari~l  mommari~l  dadmari~l     kidboy    kided12    momed12    daded12
    ---------+---------------------------------------------------------------------------
         raw |     0.000      0.000      0.000      0.000      0.000      0.000      0.000
    -----------------------------------------------------------------------------------------
```

Above: the means are recovered perfectly because each outcome has its own intercept (and predictor means are not part of the model). Below: the bolded covariances indicate the biggest sources of misfit—it looks like momed12 needs to predict each outcome!

```
Covariance residuals
             | kidmari~l  mommari~l  dadmari~l     kidboy    kided12    momed12    daded12
    ---------+---------------------------------------------------------------------------
  kidmarital |     0.002
  mommarital |     0.003      0.002
  dadmarital |     0.004      0.005      0.000
      kidboy |     0.004      0.015      0.014      0.000
     kided12 |    -0.001      0.016     -0.008      0.000      0.000
     momed12 |     0.068     -0.072     -0.280      0.000      0.000      0.000
     daded12 |    -0.000     -0.000     -0.000      0.000      0.000      0.000      0.000
    -----------------------------------------------------------------------------------------
```

```
.   estat mindices, minchi2(3.84) showpclass(all)  // Print cheat codes to improve model fit at p<.05
Modification indices
---------------------------------------------------------------
                |                                     Standard
                |        MI     df   P>MI        EPC        EPC
----------------+----------------------------------------------
Structural      |
  dadmarital <- |
     mommarital |     9.061      1   0.00    3.68633   3.692443  This is already in the model as a cov
        momed12 |     9.061      1   0.00  -.0599371  -.2888608  This is MomEd → DadMarit
---------------------------------------------------------------
EPC = expected parameter change
```

R Syntax for Previous Model 3 as a Path Model (estimated with ML; regular SEs):

```
print("R Model 3: Own Education + Dad Education a Predictor of Each Attitude")
# Create model syntax as separate text object
Syntax3 = "
# Residual variances estimated separately (by default)
  KidMarital ~~ KidMarital; MomMarital ~~ MomMarital; DadMarital ~~ DadMarital
# All possible pairwise residual covariances (not estimated by default)
  KidMarital ~~ MomMarital + DadMarital; MomMarital ~~ DadMarital
# All intercepts estimated separately (by default)
  KidMarital ~ 1; MomMarital ~ 1; DadMarital ~ 1
# Regressions: y outcomes ON x predictors (label to do math on later)
  KidMarital ~ KidBoy + KidEd12
  MomMarital ~ MomEd12
  KidMarital ~ (DadEd2K)*DadEd12
  MomMarital ~ (DadEd2M)*DadEd12
  DadMarital ~ (DadEd2D)*DadEd12
# Getting differences in effect of DadEd for each person
  KvMDadEd := DadEd2M - DadEd2K  # Kid v. Mom: Dad Educ Effect Diff
  KvDDadEd := DadEd2D - DadEd2K  # Kid v. Dad: Dad Educ Effect Diff
  MvDDadEd := DadEd2D - DadEd2M  # Mom v. Dad: Dad Educ Effect Diff
"
print("lavaan path analysis model estimated with ML on wide-format data")
PathModel3 = lavaan(data=Example5_wide, model=Syntax3, estimator="MLR", mimic="mplus")
summary(PathModel3, fit.measures=TRUE, rsquare=TRUE, standardized=TRUE, ci=TRUE)

print("Request sorted modification indices for p<.05 to troubleshoot local misfit")
modindices(object=PathModel3, sort=TRUE, minimum.value=3.84)
print("Request residual covariance matrix = leftover from observed minus predicted")
resid(object=PathModel3, type="raw") # also type="cor" for correlation matrix
```

Mplus Syntax and Output for Previous Model 3 as a Path Model (estimated with ML; regular SEs):

```
!!!!!!!!!!!!!!!!!!!!!!!!!! Mplus Lines Cannot Exceed 90 Characters !!!!!!!!!!!!!!!!!!!!
TITLE: Example 5 Model 3: Own Education + Dad Education a Predictor of Each Attitude

DATA:    FILE = PSQF6270_Example5Wide.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 = FamilyID KidBoy KidEd12 MomEd12 DadEd12 KidMarit MomMarit DadMarit;
! List of ALL variables used in model;
  USEVARIABLES = KidBoy KidEd12 MomEd12 DadEd12 KidMarit MomMarit DadMarit;
! Missing data codes (here, -999);
  MISSING = ALL (-999);

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

OUTPUT:      CINTERVAL;          ! Print confidence intervals
             STDYX;              ! Print fully standardized solution, too
             RESIDUAL;           ! Print how far off each predicted covariance is
             MODINDICES (3.84);  ! Print cheat codes to improve our model fit at p<.05

MODEL: ! * Indicates estimated parameter (all listed below for clarity)

! All residual variances estimated separately (by default)
  KidMarit* MomMarit* DadMarit*;

! All possible pairwise residual covariances (not estimated by default)
  KidMarit MomMarit DadMarit WITH KidMarit* MomMarit* DadMarit*;

! All intercepts estimated separately (by default)
  [KidMarit* MomMarit* DadMarit*];
```

```
! Regressions: y outcomes ON x predictors (label to do math on later)
  KidMarit ON KidBoy* KidEd12*;
  MomMarit ON MomEd12*;
  KidMarit MomMarit DadMarit ON DadEd12* (DadEd2K DadEd2M DadEd2D);

! Getting differences in effect of DadEd for each person
  MODEL CONSTRAINT:
  NEW (KvMDadEd KvDDadEd MvDDadEd); ! List names of linear combinations here
  KvMDadEd = DadEd2M - DadEd2K;     ! Kid v. Mom: Dad Educ Effect Diff
  KvDDadEd = DadEd2D - DadEd2K;     ! Kid v. Dad: Dad Educ Effect Diff
  MvDDadEd = DadEd2D - DadEd2M;     ! Mom v. Dad: Dad Educ Effect Diff
```

```
THE MODEL ESTIMATION TERMINATED NORMALLY
MODEL FIT INFORMATION
Number of Free Parameters                       15   Notes from Lesa:
Loglikelihood
          H0 Value                        -337.106   For OUR model: Larger is better
          H1 Value                        -331.641   For model with all possible paths estimated
Information Criteria
          Akaike (AIC)                     704.211   For our model: Smaller is better
          Bayesian (BIC)                   748.336
          Sample-Size Adjusted BIC         700.878
            (n* = (n + 2) / 24)
Chi-Square Test of Model Fit
          Value                             10.929   This is -2ΔLL for our H0-H1
          Degrees of Freedom                     6   This is counting the covariances between X's and Y's too
          P-Value                           0.0906   Test of exact fit: Nonsignificant is good!

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.077   Should be < .08 or so
          90 Percent C.I.             0.000  0.148
          Probability RMSEA <= .05           0.229   Test of close fit: Nonsignificant is good!
CFI/TLI
          CFI                                0.870   Should be > .9 or so
          TLI                                0.676   Should be > .9 or so
Chi-Square Test of Model Fit for the Baseline Model
          Value                             52.998   This is -2ΔLL for H0-H1 if H0 had no paths at all
          Degrees of Freedom                    15
          P-Value                           0.0000
SRMR (Standardized Root Mean Square Residual)
          Value                              0.046   Should be < .05 or so
```

```
MODEL RESULTS (UNSTANDARDIEZD SOLUTION; Mplus reorders them to list paths first)
                                                  Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value  IN MIXED
 KIDMARIT ON
    KIDBOY             0.264      0.091      2.886      0.004  B11
    KIDED12           -0.003      0.024     -0.109      0.913  B31
    DADED12            0.000      0.018     -0.027      0.978  B21
 MOMMARIT ON
    MOMED12           -0.016      0.021     -0.767      0.443  B42
    DADED12           -0.002      0.021     -0.081      0.935  B22
 DADMARIT ON
    DADED12           -0.055      0.016     -3.339      0.001  B20
KIDMARIT WITH
    MOMMARIT           0.038      0.027      1.424      0.154  UN(2,1)
    DADMARIT           0.076      0.026      2.893      0.004  UN(3,1)
 MOMMARIT WITH
    DADMARIT           0.084      0.027      3.066      0.002  UN(3,2)
 Intercepts
    KIDMARIT           1.512      0.099     15.290      0.000  B01
    MOMMARIT           1.937      0.063     30.949      0.000  B02
    DADMARIT           2.071      0.057     36.154      0.000  B00
 Residual Variances
    KIDMARIT           0.309      0.037      8.365      0.000  UN(1,1)
    MOMMARIT           0.316      0.038      8.339      0.000  UN(2,2)
    DADMARIT           0.294      0.035      8.367      0.000  UN(3,3)
New/Additional Parameters (FROM MODEL CONSTRAINT, like ESTIMATE or LINCOM)
    KVMDADED          -0.001      0.026     -0.046      0.963  B22 - B21
    KVDDADED          -0.054      0.021     -2.586      0.010  B20 - B21
    MVDDADED          -0.053      0.023     -2.279      0.023  B20 - B22
```

These unstandardized ON paths are the fixed slopes from MIXED.

These unstandardized WITH covariances are residual covariances (in R).

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

```
STANDARDIZED MODEL RESULTS – ALL VARIABLES HAVE MEAN=0, SD=1
STDYX Standardization
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
 KIDMARIT ON
    KIDBOY             0.231      0.078      2.950      0.003
    KIDED12           -0.009      0.083     -0.109      0.913
    DADED12           -0.002      0.086     -0.027      0.978
 MOMMARIT ON
    MOMED12           -0.078      0.102     -0.766      0.444
    DADED12           -0.008      0.102     -0.081      0.935
 DADMARIT ON
    DADED12           -0.272      0.078     -3.470      0.001
 KIDMARIT WITH
    MOMMARIT           0.122      0.084      1.455      0.146
    DADMARIT           0.252      0.079      3.187      0.001
 MOMMARIT WITH
    DADMARIT           0.275      0.080      3.433      0.001
 Intercepts
    KIDMARIT           2.646      0.247     10.723      0.000
    MOMMARIT           3.434      0.228     15.057      0.000
    DADMARIT           3.676      0.221     16.659      0.000
 Residual Variances
    KIDMARIT           0.946      0.036     26.246      0.000
    MOMMARIT           0.993      0.014     71.055      0.000
    DADMARIT           0.926      0.043     21.782      0.000
R-SQUARE
    Observed                                        Two-Tailed
    Variable        Estimate       S.E.  Est./S.E.    P-Value
    KIDMARIT           0.054      0.036      1.487      0.137
    MOMMARIT           0.007      0.014      0.496      0.620
    DADMARIT           0.074      0.043      1.735      0.083
```

These standardized ON paths are standardized regression coefficients.

These standardized WITH covariances are residual correlations (in RCORR).

```
ESTIMATED MODEL AND RESIDUALS (OBSERVED - ESTIMATED)

Residuals for Means
  KIDMARIT      MOMMARIT      DADMARIT      KIDBOY        KIDED12      MOMED12       DADED12
  ________      ________      ________      ________      ________     ________      ______
    0.000         0.000         0.000         0.000         0.000        0.000         0.000

 Residuals for Covariances
             KIDMARIT   MOMMARIT    DADMARIT   KIDBOY     KIDED12     MOMED12    DADED12
             ________   ________    ________   ________   ________    ________   ________
 KIDMARIT       0.002
 MOMMARIT       0.003      0.002
 DADMARIT       0.004      0.005       0.000
 KIDBOY         0.004      0.015       0.014      0.000
 KIDED12       -0.001      0.016      -0.008      0.000      0.000
 MOMED12        0.068     -0.072      -0.280      0.000      0.000       0.000
 DADED12        0.000      0.000       0.000      0.000      0.000       0.000      0.000
```

The means are recovered perfectly because each outcome has its own intercept (and predictor means are not part of the model).

After shutting off the MODEL CONSTRAINT code and running it again, we get these "helpful" suggestions for how to improve model fit:

The bolded covariances above indicate the biggest sources of misfit—it looks like momed12 needs to predict each outcome!

```
Minimum M.I. value for printing the modification index     3.840
                            M.I.     E.P.C.  Std E.P.C.  StdYX E.P.C.

ON Statements
DADMARIT ON MOMMARIT       9.062     3.687      3.687         3.693  This is already in the model as a cov
DADMARIT ON MOMED12        9.061    -0.060     -0.060        -0.289  This is MomEd → DadMarit

WITH Statements
MOMED12  WITH DADMARIT     9.336    -0.294     -0.294        -0.200  This is MomEd ←→ DadMarit
DADED12  WITH DADMARIT     8.134     0.491      0.491         0.324  This is already in the model as a path
```

Model 4 in Univariate Software, DV-Specific Intercepts: To what extent does mom's education also predict kid and dad attitudes? ***Uses long-format data, ML, and robust standard errors for multivariate non-normality***

$$\begin{aligned}\widehat{Marital}_{fi} = {} & \beta_{00}(Dad_{fi}) + \beta_{01}(Kid_{fi}) + \beta_{02}(Mom_{fi}) + \beta_{11}(Kid_{fi})(KidBoy_f) \\ & +\beta_{20}(Dad_{fi})(DadEd_f - 12) + \beta_{31}(Kid_{fi})(KidEd_f - 12) + \beta_{42}(Mom_{fi})(MomEd_f - 12) \\ & +\beta_{21}(Kid_{fi})(DadEd_f - 12) + \beta_{22}(Mom_{fi})(DadEd_f - 12) \\ & +\beta_{41}(Kid_{fi})(MomEd_f - 12) + \beta_{40}(Dad_{fi})(MomEd_f - 12)\end{aligned}$$

```
display "STATA Model 4: DV-Specific Intercepts -- Add Mom Educ (Controlling for Own+Dad Educ)"
display "To match path model in Part 2, switch to ML estimation, robust SEs"
display "Satterthwaite DF not allowed with EMPIRICAL, so switch to residual (N-k)"
mixed marital c.kid c.mom c.dad c.kid#c.kidboy c.kid#c.kided12 c.mom#c.momed12  ///
      c.dad#c.daded12 c.kid#c.daded12 c.mom#c.daded12                          ///
      c.kid#c.momed12 c.dad#c.momed12, noconstant                               ///
      || familyid: , noconstant   /// This NOCONSTANT removes family random intercept
      nolog mle residuals(unstructured,t(DVnum))  /// Unstructured R matrix by DV
      difficult vce(robust)         // Use robust SEs, so no denominator DF allowed
display "-2LL=" e(ll)*-2            // Print -2LL for model
estat wcorrelation, covariance      // R matrix
estat wcorrelation                  // RCORR matrix
predict pred, xb  // Add column pred of predicted outcomes to data
lincom c.kid#c.daded12*-1 + c.mom#c.daded12*1, small // Kid vs. Mom: DadEd12 Slope Diff
lincom c.kid#c.daded12*-1 + c.dad#c.daded12*1, small // Kid vs. Dad: DadEd12 Slope Diff
lincom c.mom#c.daded12*-1 + c.dad#c.daded12*1, small // Mom vs. Dad: DadEd12 Slope Diff
lincom c.kid#c.momed12*-1 + c.mom#c.momed12*1, small // Kid vs. Mom: MomEd12 Slope Diff
lincom c.kid#c.momed12*-1 + c.dad#c.momed12*1, small // Kid vs. Dad: MomEd12 Slope Diff
lincom c.mom#c.momed12*-1 + c.dad#c.momed12*1, small // Mom vs. Dad: MomEd12 Slope Diff
// Get correlation of actual and predicted outcomes to form R2
pwcorr marital pred if DV==1, sig
display "DV=1 Kid R2= " r(rho)^2  // Print R2 relative to empty model
pwcorr marital pred if DV==2, sig
display "DV=2 Mom R2= " r(rho)^2  // Print R2 relative to empty model
pwcorr marital pred if DV==3, sig
display "DV=3 Dad R2= " r(rho)^2  // Print R2 relative to empty model
```

```
print("R Model 4: DV-Specific Intercepts -- Add Mom Educ (Controlling for Own+Dad Educ)")
print("To match path model, switch to ML estimation, but robust SEs not directly available")
Model4 = gls(data=Example5, method="ML",
             model=marital~0+kid+mom+dad+ kid:KidBoy +kid:KidEd12+mom:MomEd12+dad:DadEd12
             +kid:DadEd12+mom:DadEd12 +kid:MomEd12+dad:MomEd12,
             correlation=corSymm(form=~DVnum|FamilyID),  # Unstructured correlations
             weights=varIdent(form=~1|DVnum))            # Separate variance by DV
print("Print -2LL and Results"); -2*logLik(Model4); summary(Model4)
print("Show R and RCORR matrices for first family in the data")
getVarCov(Model4, individual="3996"); corMatrix(Model4$modelStruct$corStruct)[[3]]

print("DadEd Slope Diffs -- Had to give it correct Denominator DF")
summary(glht(model=Model4, df=135, linfct=rbind(
  "Kid vs. Mom: DadEd12 Slope Diff" = c(0,0,0,0,0,0,0,-1,1,0,0),  # in order of fixed effects
  "Kid vs. Dad: DadEd12 Slope Diff" = c(0,0,0,0,0,0,1,-1,0,0,0),
  "Mom vs. Dad: DadEd12 Slope Diff" = c(0,0,0,0,0,0,1,0,-1,0,0),
  "Kid vs. Mom: MomEd12 Slope Diff" = c(0,0,0,0,0,1,0,0,0,-1,0),
  "Kid vs. Dad: MomEd12 Slope Diff" = c(0,0,0,0,0,0,0,0,0,-1,1),
  "Mom vs. Dad: MomEd12 Slope Diff" = c(0,0,0,0,0,-1,0,0,0,0,1))), test=adjusted("none"))

print("Save predicted marital attitudes and correlate with actual marital attitudes")
Example5$Pred = predict(Model4, type="response")

rPred1 = cor.test(x=Example5$Pred[which(Example5$DVnum==1)],
                  y=Example5$marital[which(Example5$DVnum==1)], method="pearson")
print("R and R2 for DV=1 Kid"); rPred1$estimate; rPred1$estimate^2

rPred2 = cor.test(x=Example5$Pred[which(Example5$DVnum==2)],
                  y=Example5$marital[which(Example5$DVnum==2)], method="pearson")
print("R and R2 for DV=2 Mom"); rPred2$estimate; rPred2$estimate^2
```

```
rPred3 = cor.test(x=Example5$Pred[which(Example5$DVnum==3)],
                  y=Example5$marital[which(Example5$DVnum==3)], method="pearson")
print("R and R2 for DV=3 Dad"); rPred3$estimate; rPred3$estimate^2
```

Model 4 in Path Model Software, DV-Specific Intercepts: To what extent does mom's education also predict kid and dad attitudes? ***uses wide-format data, ML, and "robust" standard errors for multivariate non-normality***

$$\widehat{Marital}_{fi} = \beta_{00}\left(Dad_{fi}\right) + \beta_{01}\left(Kid_{fi}\right) + \beta_{02}\left(Mom_{fi}\right) + \beta_{11}\left(Kid_{fi}\right)\left(KidBoy_f\right)$$
$$+\beta_{20}\left(Dad_{fi}\right)\left(DadEd_f - 12\right) + \beta_{31}\left(Kid_{fi}\right)\left(KidEd_f - 12\right) + \beta_{42}\left(Mom_{fi}\right)\left(MomEd_f - 12\right)$$
$$+\beta_{21}\left(Kid_{fi}\right)\left(DadEd_f - 12\right) + \beta_{22}\left(Mom_{fi}\right)\left(DadEd_f - 12\right)$$
$$+\beta_{40}\left(Dad_{fi}\right)\left(MomEd_f - 12\right) + \beta_{41}\left(Kid_{fi}\right)\left(MomEd_f - 12\right)$$

```
display "STATA Model 4: Own + Dad & Mom Education a Predictor of Each Attitude"
display "Using SEM to create path analysis model estimated with ML on wide-format data"
sem                                           ///
   (kidmarit mommarit dadmarit <- _cons)      /// All intercepts estimated (by default)
   (kidmarit <- kidboy kided12)               /// Regressions: y outcomes ON x predictors
   (kidmarit mommarit dadmarit <- daded12)    ///
   (kidmarit mommarit dadmarit <- momed12),   /// New effects go here
    var(e.kidmarit e.mommarit e.dadmarit)     /// All residual variances estimated (by default)
    covariance(e.kidmarit*e.mommarit          /// All pairwise residual covariances (not default)
               e.mommarit*e.dadmarit          ///
               e.kidmarit*e.dadmarit)         ///
    method(mlmv) vce(robust)                   // Full-information ML and robust SEs
    lincom _b[mommarital:daded12] - _b[kidmarital:daded12] // Kid v. Mom: Dad Educ Effect Diff
    lincom _b[dadmarital:daded12] - _b[kidmarital:daded12] // Kid v. Dad: Dad Educ Effect Diff
    lincom _b[dadmarital:daded12] - _b[mommarital:daded12] // Mom v. Dad: Dad Educ Effect Diff
    lincom _b[mommarital:momed12] - _b[kidmarital:momed12] // Kid v. Mom: Mom Educ Effect Diff
    lincom _b[dadmarital:momed12] - _b[kidmarital:momed12] // Kid v. Dad: Mom Educ Effect Diff
    lincom _b[dadmarital:momed12] - _b[mommarital:momed12] // Mom v. Dad: Mom Educ Effect Diff
    sem, coeflegend                         // Print parameter labels, too (to use in lincom)
    sem, standardized                       // Print fully standardized solution, too
    estat gof, stats(all)                   // Print fit statistics
    display "LL for H1 Model= " e(critvalue_s)
    display "# of parameters= " e(df_m)
    display "-2LL= " e(ll)*-2               // Print -2LL for model
    estat eqgof                             // Print R2 per variable
    estat residuals                         // Print how far off each predicted covariance is
    estat mindices, minchi2(3.84) showpclass(all) // Print cheat codes to improve model fit p<.05
```

```
!!!!!!!!!!!!!!!!!!!!!!!!!!! Mplus Lines Cannot Exceed 90 Characters !!!!!!!!!!!!!!!!!!!!
TITLE: Example 5 Model 4: Own Ed + Dad & Mom Ed a Predictor of Each Attitude
```

DATA, VARIABLE, and OUTPUT are the same as Model 3 except for `ANALYSIS: ESTIMATOR = MLR;`

```
MODEL: ! * --> Estimated parameter (all listed below for clarity)

! All residual variances estimated separately (by default)
  KidMarit* MomMarit* DadMarit*;

! All possible pairwise residual covariances (not estimated by default)
  KidMarit MomMarit DadMarit WITH KidMarit* MomMarit* DadMarit*;

! All intercepts estimated separately (by default)
  [KidMarit* MomMarit* DadMarit*];

! Regressions: y outcomes ON x predictors (label to do math on later)
  KidMarit ON KidBoy* KidEd12*;
  KidMarit MomMarit DadMarit ON DadEd12* (DadEd2K DadEd2M DadEd2D);
  KidMarit MomMarit DadMarit ON MomEd12* (MomEd2K MomEd2M MomEd2D); ! New effects here
```

```
! Getting differences in effect of DadEd for each person
  MODEL CONSTRAINT: ! List names of linear combinations here
  NEW (KvMDadEd KvDDadEd MvDDadEd KvMMomEd KvDMomEd MvDMomEd);
  KvMDadEd = DadEd2M - DadEd2K;     ! Kid v. Mom: Dad Educ Effect Diff
  KvDDadEd = DadEd2D - DadEd2K;     ! Kid v. Dad: Dad Educ Effect Diff
  MvDDadEd = DadEd2D - DadEd2M;     ! Mom v. Dad: Dad Educ Effect Diff
  KvMMomEd = MomEd2M - MomEd2K;     ! Kid v. Mom: Mom Educ Effect Diff
  KvDMomEd = MomEd2D - MomEd2K;     ! Kid v. Dad: Mom Educ Effect Diff
  MvDMomEd = MomEd2D - MomEd2M;     ! Mom v. Dad: Mom Educ Effect Diff


print("R Model 4: Own + Dad + Mom Education a Predictor of Each Attitude")
# Create model syntax as separate text object
Syntax4 = "
# Residual variances estimated separately (by default)
  KidMarital ~~ KidMarital; MomMarital ~~ MomMarital; DadMarital ~~ DadMarital
# All possible pairwise residual covariances (not estimated by default)
  KidMarital ~~ MomMarital + DadMarital; MomMarital ~~ DadMarital
# All intercepts estimated separately (by default)
  KidMarital ~ 1; MomMarital ~ 1; DadMarital ~ 1

# Regressions: y outcomes ON x predictors (label to do math on later)
  KidMarital ~ KidBoy + KidEd12
  KidMarital ~ (DadEd2K)*DadEd12
  MomMarital ~ (DadEd2M)*DadEd12
  DadMarital ~ (DadEd2D)*DadEd12
# New effects here
  KidMarital ~ (MomEd2K)*MomEd12
  MomMarital ~ (MomEd2M)*MomEd12
  DadMarital ~ (MomEd2D)*MomEd12

# Getting differences in effect of DadEd for each person
  KvMDadEd := DadEd2M - DadEd2K;  # Kid v. Mom: Dad Educ Effect Diff
  KvDDadEd := DadEd2D - DadEd2K;  # Kid v. Dad: Dad Educ Effect Diff
  MvDDadEd := DadEd2D - DadEd2M;  # Mom v. Dad: Dad Educ Effect Diff
  KvMMomEd := MomEd2M - MomEd2K;  # Kid v. Mom: Mom Educ Effect Diff
  KvDMomEd := MomEd2D - MomEd2K;  # Kid v. Dad: Mom Educ Effect Diff
  MvDMomEd := MomEd2D - MomEd2M;  # Mom v. Dad: Mom Educ Effect Diff
"

print("lavaan path analysis model estimated with ML on wide-format data")
PathModel4 = lavaan(data=Example5_wide, model=Syntax4, estimator="MLR", mimic="mplus")
summary(PathModel4, fit.measures=TRUE, rsquare=TRUE, standardized=TRUE, ci=TRUE)
print("Request sorted modification indices for p<.05 to troubleshoot local misfit")
modindices(object=PathModel4, sort=TRUE, minimum.value=3.84)
print("Request residual correlation matrix =leftover from observed minus predicted")
resid(object=PathModel4, type="raw") # also type="cor" for correlation matrix
```

R LAVAAN Output—shows both regular ML and "robust" ML fit statistics:

```
Estimator                                         ML
  Optimization method                         NLMINB
  Number of model parameters                      17
  Number of observations                         140
  Number of missing patterns                       1

Model Test User Model:
                                              Standard      Robust
  Test Statistic                                 1.034       1.026   This is -2ΔLL for our H0-H1
  Degrees of freedom                                 4           4
  P-value (Chi-square)                           0.905       0.906
  Scaling correction factor                                  1.007
       Yuan-Bentler correction (Mplus variant)

Model Test Baseline Model:
  Test statistic                               52.998      52.902
  Degrees of freedom                               15          15
  P-value                                       0.000       0.000
  Scaling correction factor                                 1.002
```

```
User Model versus Baseline Model:
  Comparative Fit Index (CFI)                    1.000       1.000  Want close to 1
  Tucker-Lewis Index (TLI)                       1.293       1.294
  Robust Comparative Fit Index (CFI)                         1.000
  Robust Tucker-Lewis Index (TLI)                            1.296

Loglikelihood and Information Criteria:
  Loglikelihood user model (H0)               -332.158    -332.158  For our model: Larger is better
  Scaling correction factor                                  1.007  1=multivariate normality (so not bad!)
      for the MLR correction
  Loglikelihood unrestricted model (H1)       -331.641    -331.641  For model with all paths estimated
  Scaling correction factor                                  1.007
      for the MLR correction

  Akaike (AIC)                                 698.316     698.316  For our model: Smaller is better
  Bayesian (BIC)                               748.324     748.324  For our model: Smaller is better
  Sample-size adjusted Bayesian (BIC)          694.538     694.538  For our model: Smaller is better

Root Mean Square Error of Approximation:
  RMSEA                                          0.000       0.000  Want close to 0
  90 Percent confidence interval - lower         0.000       0.000
  90 Percent confidence interval - upper         0.052       0.051
  P-value RMSEA <= 0.05                          0.947       0.948  Test of RMSEA <=.05

  Robust RMSEA                                               0.000
  90 Percent confidence interval - lower                     0.000
  90 Percent confidence interval - upper                     0.052

Standardized Root Mean Square Residual:
  SRMR                                           0.016       0.016  Want close to 0
```

Parameter estimates, their SEs, and standardized estimates would be Table 1

```
Regressions:  -- THESE ARE THE FIXED SLOPES FROM MIXED
                   Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.upper   Std.lv  Std.all=STDYX IN MPLUS
  KidMarital ~
    KidBoy            0.258    0.093    2.786    0.005    0.076    0.439    0.258    0.225  B11
    KidEd12          -0.011    0.024   -0.441    0.659   -0.058    0.037   -0.011   -0.037  B31
    DadEd12 (DE2K)   -0.007    0.020   -0.367    0.714   -0.046    0.032   -0.007   -0.035  B21
  MomMarital ~
    DadEd12 (DE2M)    0.006    0.020    0.316    0.752   -0.033    0.046    0.006    0.031  B22
  DadMarital ~
    DadEd12 (DE2D)   -0.024    0.017   -1.388    0.165   -0.057    0.010   -0.024   -0.117  B20
  KidMarital ~
    MomEd12 (ME2K)    0.015    0.022    0.681    0.496   -0.028    0.059    0.015    0.072  B41
  MomMarital ~
    MomEd12 (ME2M)   -0.031    0.022   -1.412    0.158   -0.073    0.012   -0.031   -0.148  B42
  DadMarital ~
    MomEd12 (ME2D)   -0.056    0.019   -2.974    0.003   -0.094   -0.019   -0.056   -0.272  B40

Covariances: -- THESE ARE RESIDUAL COVARIANCES FROM R MATRIX OFF-DIAGONALS
                   Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.upper   Std.lv  Std.all
 .KidMarital ~~
   .MomMarital        0.039    0.028    1.400    0.162   -0.016    0.094    0.039    0.126  UN(1,2)
   .DadMarital        0.080    0.024    3.296    0.001    0.033    0.128    0.080    0.274  UN(1,3)
 .MomMarital ~~
   .DadMarital        0.080    0.020    4.011    0.000    0.041    0.119    0.080    0.270  UN(2,3)

Intercepts: -- THESE ARE THE FIXED INTERCEPTS FROM MIXED
                   Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.upper   Std.lv  Std.all
   .KidMarital        1.522    0.101   15.125    0.000    1.325    1.719    1.522    2.664  B01
   .MomMarital        1.951    0.063   30.825    0.000    1.827    2.075    1.951    3.445  B02
   .DadMarital        2.123    0.060   35.574    0.000    2.006    2.240    2.123    3.769  B00

Variances: -- THESE ARE THE RESIDUAL VARIANCES FROM R MATRIX DIAGONAL
                   Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.upper   Std.lv  Std.all
   .KidMarital        0.308    0.031   10.096    0.000    0.248    0.368    0.308    0.944  UN(1,1)
   .MomMarital        0.315    0.045    7.081    0.000    0.228    0.402    0.315    0.983  UN(2,2)
   .DadMarital        0.278    0.034    8.092    0.000    0.211    0.345    0.278    0.876  UN(3,3)

R-Square: -- THESE ARE CLOSE TO BUT NOT THE SAME AS WAS FOUND IN THE UNIVARIATE MODELS
                   Estimate
    KidMarital        0.056
    MomMarital        0.017
    DadMarital        0.124
```

```
Defined Parameters: -- THESE ARE ESTIMATE/LINCOM/GLHT/MODEL CONSTRAINT LINEAR COMBINATIONS
                   Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.upper   Std.lv  Std.all
    KvMDadEd          0.014    0.026    0.522    0.602   -0.038    0.065    0.014    0.067  B22 - B21
    KvDDadEd         -0.016    0.022   -0.741    0.459   -0.059    0.027   -0.016   -0.081  B20 - B21
    MvDDadEd         -0.030    0.025   -1.212    0.225   -0.078    0.018   -0.030   -0.148  B20 - B22
    KvMMomEd         -0.046    0.029   -1.569    0.117   -0.103    0.011   -0.046   -0.219  B42 - B41
    KvDMomEd         -0.072    0.027   -2.657    0.008   -0.124   -0.019   -0.072   -0.344  B40 - B41
    MvDMomEd         -0.026    0.025   -1.041    0.298   -0.074    0.023   -0.026   -0.124  B40 - B42


$cov - THESE ARE THE DISCREPANCIES FOR OBSERVED MINUS PREDICTED COVARIANCES
           KdMrtl MmMrtl DdMrtl KidBoy KdEd12 DdEd12 MmEd12
KidMarital 0.002
MomMarital 0.004  0.000
DadMarital 0.003  0.000  0.000
KidBoy     0.005  0.015  0.015  0.000
KidEd12    0.013  0.029  0.043  0.000  0.000
DadEd12    0.000  0.000  0.000  0.000  0.000  0.000
MomEd12    0.000  0.000  0.000  0.000  0.000  0.000  0.000

$mean
KidMarital MomMarital DadMarital     KidBoy     KidEd12     DadEd12     MomEd12
         0          0          0          0           0           0           0
```

Only the kid predictors on the mom and dad outcomes have leftover covariance, and no single added paths would help the model.

Example results section for Part 2 Models 3–4 [picking up from Part 1; using R LAVAAN output]:

Next, we examined whether father's education incrementally predicted the marital attitudes of the mother or adult child after controlling for their own education, but neither effect was significant (and the effect of father's education on his own attitudes was significantly larger). The effect of father's education on his own attitudes remained significant, while the effect of education on their own attitudes for the adult child and mother remained nonsignificant).

Finally, we examined the incremental effects of mother's education on marital attitudes, and results from this final model are shown in Table 1. For every additional year of mother's education, father's attitudes were expected to be significantly less conservative by 0.056 (p = .003). The effect of mother's education on the adult child attitudes was nonsignificant and significantly smaller than its effect on father's attitudes.

We re-estimated the final model as a path analysis in the R package lavaan (using robust maximum likelihood) in order to obtain indices of absolute model fit. The model had excellent fit, $\chi^2(4) = 1.026$, p = .906, RMSEA = .00 [CI = .00–.051], CFI = 1.00, indicating that no further paths were needed. This final model is depicted in Figure 1 below.

Figure 1 (line types used to help visually distinguish the paths; standardized coefficients may also be added)