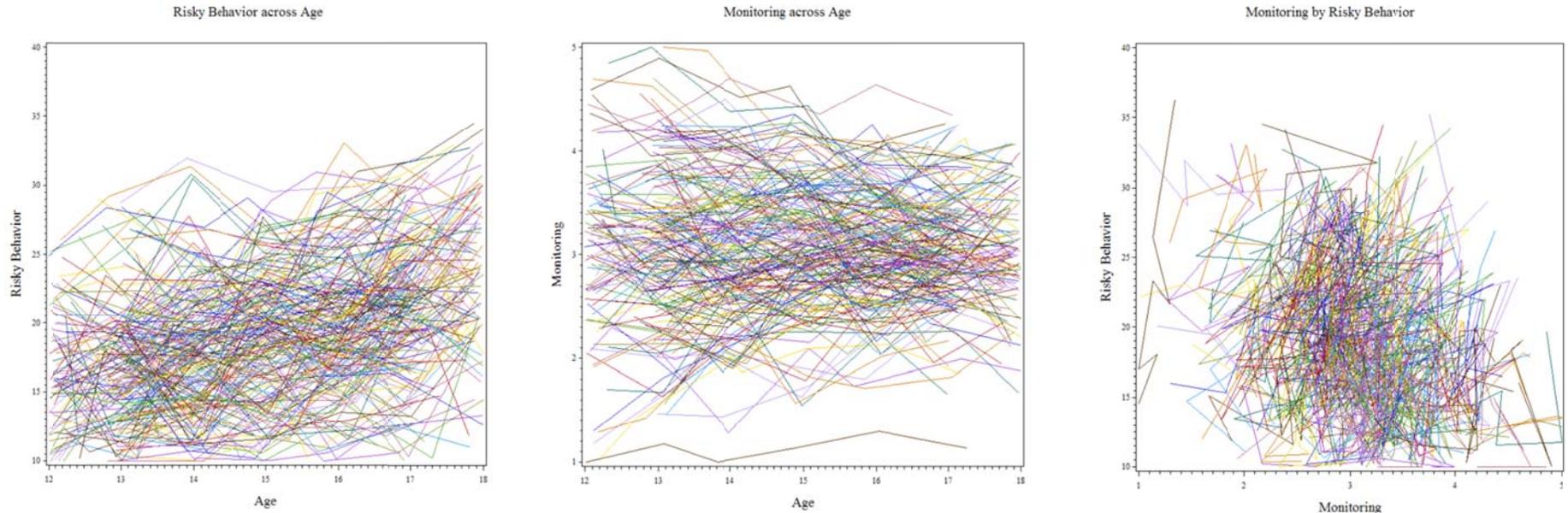


Seven Ways of Estimating Multivariate Change in SAS PROC MIXED, SAS PROC NL MIXED, and Mplus v. 7.11

These simulated data are from Hoffman chapter 9, and include 200 girls measured approximately annually from ages 12–18 (time 0 = age 18) on their risky behavior (the outcome, a sum ranging from 10 to 50) and the extent to which their mothers monitored their activities (the time-varying predictor, a mean ranging from 1 to 5, centered at 3). A time-invariant predictor of the conservativeness of mothers’ attitudes about the smoking and drinking (a mean ranging from 1 to 5, centered at 4) was also collected at the age 12 occasion. Here are the individual growth trajectories for risky behavior and monitoring:



Level 1 :

Multivariate Growth Model

$$y_{tid} = dvR \left[\beta_{0iR} + \beta_{1iR} (Age_{tiR} - 18) + \beta_{2iR} (Age_{tiR} - 18)^2 + e_{tiR} \right] + dvM \left[\beta_{0iM} + \beta_{1iM} (Age_{tiM} - 18) + e_{tiM} \right]$$

Level 2 :

- Risky Intercept: $\beta_{0iR} = \gamma_{00R} + \gamma_{01R} (Attitudes12_i - 4) + U_{0iR}$
- Risky Age: $\beta_{1iR} = \gamma_{10R} + \gamma_{11R} (Attitudes12_i - 4) + U_{1iR}$
- Risky Age²: $\beta_{2iR} = \gamma_{20R}$
- Monitor Intercept: $\beta_{0iM} = \gamma_{00M} + U_{0iM}$
- Monitor Age: $\beta_{1iM} = \gamma_{10M} + U_{1iM}$

The best-fitting unconditional longitudinal model included fixed quadratic and random linear effects of age for risky behavior, but a random linear effect of age for monitoring (although the fixed linear age slope was nonsignificant). In addition, mother’s attitudes significantly predicted the intercept and linear age slope for risky behavior, but did not significantly predict monitoring.

Chapter 9 began with person-mean-centering and baseline-centering of monitoring of a time-varying predictor of risky behavior. Both were shown to be inadequate because they do not properly distinguish the intercept, linear age slope, and residual variance contained in the monitoring predictor, each of which could potentially relate to those of risky behavior. So the purpose of this example is to demonstrate multilevel, SEM, and “multilevel SEM” methods of estimating models of multivariate change. In total, we will examine six models, some of which will be statistically equivalent, some of which will not, so that you can decide what will be most optimal for your own data.

Multivariate Growth Model for Risky Behavior and Monitoring in SAS, controlling risky behavior for attitudes (Model #1):

```
* Stack longitudinal data into multivariate longitudinal;
DATA RiskyStacked2; SET RiskyStacked;
DV="1risky "; dvR=1; dvM=0; outcome=risky; OUTPUT;
DV="2monitor"; dvR=0; dvM=1; outcome=monitor3; OUTPUT;
RUN;

TITLE1 "Multivariate Model at Age 18 = Time 0";
PROC MIXED DATA=RiskyStacked2 NOITPRINT NOCLPRINT COVTEST
IC NOINFO NAMELEN=100 METHOD=ML;
CLASS FamilyID occasion DV;

MODEL outcome = dvR dvM dvR*agec18 dvM*agec18
           dvR*agec18*agec18 dvR*att4 dvR*att4*agec18
           / NOINT SOLUTION DDFM=Satterthwaite NOTEST;

RANDOM dvR dvM dvR*agec18 dvM*agec18
       / G GCORR TYPE=UN SUBJECT=FamilyID;

REPEATED DV / R RCORR TYPE=UN SUBJECT=occasion*FamilyID;
RUN; TITLE1;

* Sending original longitudinal data to Mplus;
DATA Mplus; SET RiskyStacked;
agesq=agec18*agec18; mon3=monitor-3;
KEEP FamilyID occasion age monitor risky agec18 att4
      PMmon3 WPmon age18Mon3 Change18Mon agesq mon3;
RUN;

* Export to .csv for use in Mplus;
PROC EXPORT DATA=work.Mplus
OUTFILE= "&example.\chapter9v3.csv"
DBMS=CSV REPLACE; PUTNAMES=NO; RUN;
```

Mplus results start here: This is the same model...

MODEL FIT INFORMATION	
Number of Free Parameters	20
Loglikelihood	
H0 Value	-4392.253
Information Criteria	
Akaike (AIC)	8824.506
Bayesian (BIC)	8929.390
Sample-Size Adjusted BIC	8865.858
(n* = (n + 2) / 24)	

In Mplus, doing the same thing as a multivariate multilevel model (#2):

```
TITLE: Multivariate Growth Model as MLM
DATA: FILE = chapter9v3.csv; ! Syntax in same folder as data
VARIABLE:
! List of variables in data file
NAMES = FamilyID occasion age monitor risky age18 att4
        PMmon3 WPmon Age18M3 C18Mon agesq mon3;
! Variables to be analyzed in this model
USEVARIABLE = age18 agesq att4 risky mon3;
MISSING ARE ALL (-999); ! Missing data identifier
! MLM options
CLUSTER = FamilyID; ! Level-2 ID
BETWEEN = att4; ! Observed ONLY level-2 predictors
WITHIN = age18 agesq; ! Observed ONLY level-1 predictors

ANALYSIS: TYPE = TWOLEVEL RANDOM; ESTIMATOR = ML;
MODEL: ! R = risky behavior, M = monitoring
%WITHIN%
risky* mon3* (Rresvar Mresvar); ! Residual variances
Rslp | risky ON age18*; ! R linear age slope
Rquad | risky ON agesq*; ! R quadratic age slope
Mslp | mon3 ON age18*; ! M linear age slope
risky WITH mon3* (ResCov); ! Residual covariance

%BETWEEN%
risky* mon3* (Rintvar Mintvar); ! Intercept variances
Rslp* Mslp* (Rslpvar Mslpvar); ! Linear age slope variances
Rquad@0; ! No quadratic age slope variance
[risky* mon3*]; ! Fixed intercepts
[Rquad* Rslp* Mslp*]; ! Fixed age slopes
risky Rslp ON att4*; ! Att --> R int, linear age slope
risky WITH Rslp* (RIntSlp); ! R Int-slope covariance
mon3 WITH Mslp* (MIntSlp); ! M Int-slope covariance

risky WITH mon3* (IntCov); ! Intercept covariance
Rslp WITH Mslp* (SlpCov); ! Slope covariance
mon3 WITH Rslp* (Int2Slp); ! M int, R slope covariance
Mslp WITH risky* (Slp2Int); ! M slope, R int covariance

MODEL CONSTRAINT: ! Estimating correlations
NEW(ResCor IntCor SlpCor RIScor MIScor I2Scor S2ICor);
ResCor = ResCov / (SQRT(Rresvar)*SQRT(Mresvar));
IntCor = IntCov / (SQRT(Rintvar)*SQRT(Mintvar));
SlpCor = SlpCov / (SQRT(Rslpvar)*SQRT(Mslpvar));
RIScor = RIntSlp / (SQRT(Rintvar)*SQRT(Rslpvar));
MIScor = MIntSlp / (SQRT(Mintvar)*SQRT(Mslpvar));
I2Scor = Int2Slp / (SQRT(Mintvar)*SQRT(Rslpvar));
S2Icor = Slp2Int / (SQRT(Mslpvar)*SQRT(Rintvar));
```

SAS multivariate MLM Results:

Estimated R Matrix for FamilyID*occasion 1 12			Estimated R Correlation Matrix for FamilyID*occasion 1 12		
Row	Col1	Col2	Row	Col1	Col2
1	8.3538	0.2874	1	1.0000	0.3499
2	0.2874	0.08077	2	0.3499	1.0000

Estimated G Matrix						
Row	Effect	Family ID	Col1	Col2	Col3	Col4
1	dvR	1	18.0644	-0.8554	1.8829	0.04072
2	dvM	1	-0.8554	0.1953	-0.1064	-0.00047
3	dvR*agec18	1	1.8829	-0.1064	0.4883	-0.01815
4	dvM*agec18	1	0.04072	-0.00047	-0.01815	0.01049

Estimated G Correlation Matrix						
Row	Effect	Family ID	Col1	Col2	Col3	Col4
1	dvR	1	1.0000	-0.4554	0.6340	0.09356
2	dvM	1	-0.4554	1.0000	-0.3446	-0.01043
3	dvR*agec18	1	0.6340	-0.3446	1.0000	-0.2537
4	dvM*agec18	1	0.09356	-0.01043	-0.2537	1.0000

Covariance Parameter Estimates						
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z	
UN(2,1)	FamilyID	-0.8554	0.1685	-5.08	<.0001	
UN(3,1)	FamilyID	1.8829	0.3564	5.28	<.0001	
UN(3,2)	FamilyID	-0.1064	0.03086	-3.45	0.0006	
UN(4,1)	FamilyID	0.04072	0.03879	1.05	0.2939	
UN(4,2)	FamilyID	-0.00047	0.004005	-0.12	0.9062	
UN(4,3)	FamilyID	-0.01815	0.007344	-2.47	0.0135	
UN(2,1)	FamilyID*occasion	0.2874	0.02753	10.44	<.0001	

Information Criteria						
Neg2LogLike	Parms	AIC	AICC	HQIC	BIC	CAIC
8784.5	20	8824.5	8824.8	8851.2	8890.5	8910.5

Solution for Fixed Effects						
Effect	Estimate	Standard Error	DF	t Value	Pr > t	
dvR	23.3138	0.3477	239	67.06	<.0001	
dvM	0.06505	0.03412	200	1.91	0.0580	
dvR*agec18	1.9743	0.1386	1185	14.25	<.0001	
dvM*agec18	-0.00328	0.008176	200	-0.40	0.6884	
dvR*agec18*agec18	0.1466	0.02058	1010	7.12	<.0001	
dvR*Att4	-3.3328	0.5126	199	-6.50	<.0001	
dvR*agec18*Att4	-0.5298	0.1025	199	-5.17	<.0001	

Mplus results continue: This is the same model...

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
RISKY WITH MON3	0.287	0.028	10.441	0.000
Residual Variances MON3	0.081	0.004	22.354	0.000
RISKY	8.352	0.374	22.351	0.000
Between Level				
RSLP ON ATT4	-0.530	0.103	-5.161	0.000
RISKY ON ATT4	-3.333	0.514	-6.491	0.000
RISKY WITH RSLP	1.879	0.356	5.272	0.000
MON3 WITH MSLP	0.000	0.004	-0.118	0.906
RSLP	-0.106	0.031	-3.445	0.001
RSLP WITH MSLP	-0.018	0.007	-2.475	0.013
MSLP WITH RISKY	0.041	0.039	1.049	0.294
RISKY WITH MON3	-0.855	0.168	-5.076	0.000
Means				
MON3	0.065	0.034	1.907	0.057
RQUAD	0.147	0.021	7.117	0.000
MSLP	-0.003	0.008	-0.402	0.688
Intercepts				
RISKY	23.314	0.348	67.062	0.000
RSLP	1.974	0.138	14.255	0.000
Variances				
MON3	0.195	0.023	8.376	0.000
RQUAD	0.000	0.000	999.000	999.000
MSLP	0.010	0.001	7.803	0.000
Residual Variances				
RISKY	18.060	2.204	8.195	0.000
RSLP	0.485	0.080	6.071	0.000
New/Additional Parameters				
RESCOR	0.350	0.028	12.607	0.000
INTCOR	-0.455	0.074	-6.124	0.000
SLPCOR	-0.255	0.103	-2.480	0.013
RISCOR	0.635	0.057	11.087	0.000
MISCOR	-0.010	0.089	-0.117	0.906
I2SCOR	-0.346	0.095	-3.642	0.000
S2ICOR	0.094	0.087	1.071	0.284

In Mplus again, doing the same thing as SEM. Note that the original multivariate data file (one row per person) is used. Age12–Age18 are exact age variables centered so time 0 = age 18. (Model #3)

```

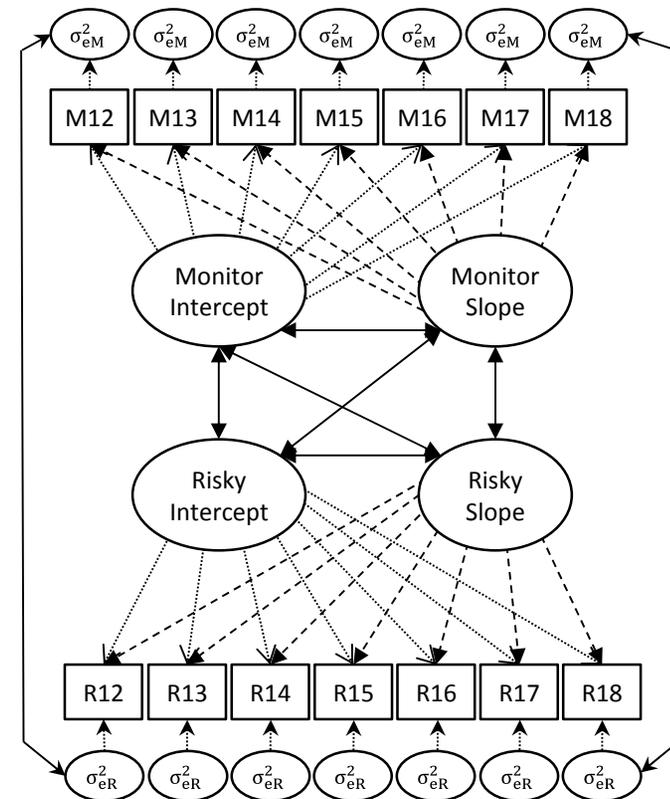
TITLE: Multivariate Growth Model as SEM
DATA: FILE = ch9multiv.csv; ! Syntax in same folder as data
VARIABLE:
! List of variables in data file
  NAMES = FamilyID att4 risky12-risky18 age12-age18 mon12-mon18;
! Variables to be analyzed in this model
  USEVARIABLE = att4 age12-age18 mon12-mon18 risky12-risky18;
  MISSING ARE ALL (-999); ! Missing data identifier
  TSCORES = age12-age18; ! Exact time indicator
ANALYSIS: TYPE = RANDOM; ESTIMATOR = ML;
MODEL: ! R = risky behavior, M = monitoring
! Risky behavior growth model using exact age as loadings
Rint Rslp Rquad | risky12-risky18 AT age12-age18;
Rint* Rslp* (Rintvar Rslpvar); ! R Int and slope variances
Rquad@0; ! No R random quadratic variance
Rint WITH Rslp* (RIntSlp); ! R Int-slope covariance
[Rint* Rslp* Rquad*]; ! R fixed growth effects
[risky12-risky18@0]; ! R Intercepts fixed to 0
risky12-risky18* (Rresvar); ! R Residual var held equal
Rint Rslp ON att4*; ! Attitudes --> risky int, slope

! Monitoring growth model using exact age as loadings
Mint Mslp | mon12-mon18 AT age12-age18;
Mint* Mslp* (Mintvar Mslpvar); ! M Int and slope variances
Mint WITH Mslp* (MIntSlp); ! M Int-slope covariance
[Mint* Mslp*]; ! M fixed growth effects
[mon12-mon18@0]; ! M Intercepts fixed to 0
mon12-mon18* (Mresvar); ! M Residual var held equal

! Covariances between outcomes
Rint WITH Mint* (IntCov); ! Intercept covariance
Rslp WITH Mslp* (SlpCov); ! Slope covariance
Mint WITH Rslp* (Int2Slp); ! M int, R slope covariance
Mslp WITH Rint* (Slp2Int); ! M slope, R int covariance
! Residual cov between same ages, held equal across age
mon12-mon18 PWITH risky12-risky18* (ResCov);

MODEL CONSTRAINT: ! Estimating correlations
NEW(ResCor IntCor SlpCor RIScor MIScor I2SCor S2ICor);
ResCor = ResCov / (SQRT(Rresvar)*SQRT(Mresvar));
IntCor = IntCov / (SQRT(Rintvar)*SQRT(Mintvar));
SlpCor = SlpCov / (SQRT(Rslpvar)*SQRT(Mslpvar));
RIScor = RIntSlp / (SQRT(Rintvar)*SQRT(Rslpvar));
MIScor = MIntSlp / (SQRT(Mintvar)*SQRT(Mslpvar));
I2SCor = Int2Slp / (SQRT(Mintvar)*SQRT(Rslpvar));
S2ICor = Slp2Int / (SQRT(Mslpvar)*SQRT(Rintvar));
  
```

Here is my “latent growth curve structural equation model”:



- > Indicates paths fixed = 1
- > Indicates paths fixed = time values
- ====> Indicates paths freely estimated
- ====> Indicates paths freely estimated between residuals at the same occasion but held equal over time

If you have balanced time, the growth model would become this:

```

Mint Mslp | mon12@-6 mon13@-5 mon14@-4 mon15@-3
           mon16@-2 mon17@-1 mon18@0;
  
```

Mplus results for SEM with correlated growth curves:

MODEL FIT INFORMATION						Means				
Number of Free Parameters		20				RQUAD	0.147	0.021	7.117	0.000
Loglikelihood						MINT	0.065	0.034	1.906	0.057
H0 Value		-4392.253				MSLP	-0.003	0.008	-0.402	0.688
Information Criteria						Intercepts				
Akaike (AIC)		8824.506				MON12	0.000	0.000	999.000	999.000
Bayesian (BIC)		8890.472				MON13	0.000	0.000	999.000	999.000
Sample-Size Adjusted BIC		8827.110				MON14	0.000	0.000	999.000	999.000
(n* = (n + 2) / 24)						MON15	0.000	0.000	999.000	999.000
MODEL RESULTS						MON16	0.000	0.000	999.000	999.000
		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	MON17	0.000	0.000	999.000	999.000
RINT	ON					MON18	0.000	0.000	999.000	999.000
ATT4		-3.333	0.514	-6.491	0.000	RISKY12	0.000	0.000	999.000	999.000
RSLP	ON					RISKY13	0.000	0.000	999.000	999.000
ATT4		-0.530	0.103	-5.161	0.000	RISKY14	0.000	0.000	999.000	999.000
RINT	WITH					RISKY15	0.000	0.000	999.000	999.000
RSLP		1.879	0.356	5.272	0.000	RISKY16	0.000	0.000	999.000	999.000
MINT		-0.855	0.168	-5.076	0.000	RISKY17	0.000	0.000	999.000	999.000
						RISKY18	0.000	0.000	999.000	999.000
MINT	WITH					RINT	23.314	0.348	67.062	0.000
MSLP		0.000	0.004	-0.118	0.906	RSLP	1.974	0.138	14.255	0.000
RSLP		-0.106	0.031	-3.445	0.001	Variances				
RSLP	WITH					RQUAD	0.000	0.000	999.000	999.000
MSLP		-0.018	0.007	-2.475	0.013	MINT	0.195	0.023	8.376	0.000
MSLP	WITH					MSLP	0.010	0.001	7.803	0.000
RINT		0.041	0.039	1.049	0.294	Residual Variances				
MON12	WITH					MON12	0.081	0.004	22.354	0.000
RISKY12		0.287	0.028	10.441	0.000	MON13	0.081	0.004	22.354	0.000
MON13	WITH					MON14	0.081	0.004	22.354	0.000
RISKY13		0.287	0.028	10.441	0.000	MON15	0.081	0.004	22.354	0.000
MON14	WITH					MON16	0.081	0.004	22.354	0.000
RISKY14		0.287	0.028	10.441	0.000	MON17	0.081	0.004	22.354	0.000
MON15	WITH					MON18	0.081	0.004	22.354	0.000
RISKY15		0.287	0.028	10.441	0.000	RISKY12	8.352	0.374	22.351	0.000
MON16	WITH					RISKY13	8.352	0.374	22.351	0.000
RISKY16		0.287	0.028	10.441	0.000	RISKY14	8.352	0.374	22.351	0.000
MON17	WITH					RISKY15	8.352	0.374	22.351	0.000
RISKY17		0.287	0.028	10.441	0.000	RISKY16	8.352	0.374	22.351	0.000
MON18	WITH					RISKY17	8.352	0.374	22.351	0.000
RISKY18		0.287	0.028	10.441	0.000	RISKY18	8.352	0.374	22.351	0.000
						RINT	18.060	2.204	8.195	0.000
						RSLP	0.485	0.080	6.071	0.000
						New/Additional Parameters				
						RESCOR	0.350	0.028	12.607	0.000
						INTCOR	-0.455	0.074	-6.124	0.000
						SLPCOR	-0.255	0.103	-2.480	0.013
						RISCOR	0.635	0.057	11.087	0.000
						MISCOR	-0.010	0.089	-0.117	0.907
						I2SCOR	-0.346	0.095	-3.642	0.000
						S2ICOR	0.094	0.087	1.071	0.284

In Mplus again, doing the same thing as a directed path SEM (Model #4).

```

TITLE: Multivariate Growth Model as Directed SEM
DATA: FILE = ch9multiv.csv; ! Syntax in same folder as data
VARIABLE:
! List of variables in data file
  NAMES = FamilyID att4 risky12-risky18 age12-age18 mon12-mon18;
! Variables to be analyzed in this model
  USEVARIABLE = att4 age12-age18 mon12-mon18 risky12-risky18;
  MISSING ARE ALL (-999); ! Missing data identifier
  TSCORES = age12-age18; ! Exact time indicator
ANALYSIS: TYPE = RANDOM; ESTIMATOR = ML;
MODEL: ! R = risky behavior, M = monitoring
! Risky behavior growth model using exact age as loadings
Rint Rslp Rquad | risky12-risky18 AT age12-age18;
Rint* Rslp* (Rintvar Rslpvar); ! R Int and slope variances
Rquad@0; ! No R random quadratic variance
Rint WITH Rslp* (RIntSlp); ! R Int-slope covariance
[Rint* Rslp* Rquad*]; ! R fixed growth effects
[risky12-risky18@0]; ! R Intercepts fixed to 0
risky12-risky18* (Rresvar); ! R Residual var held equal
Rint Rslp ON att4*; ! Attitudes --> risky int, slope

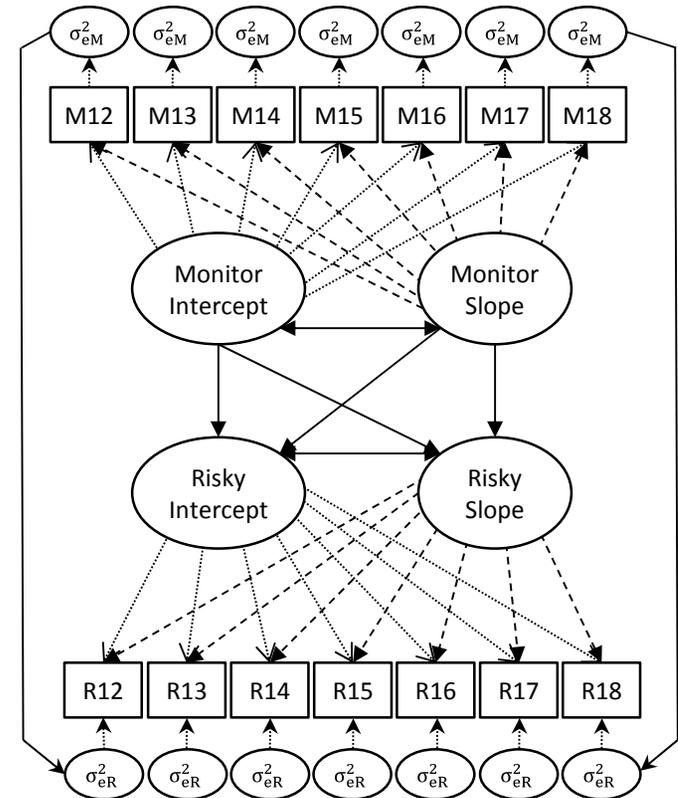
! Monitoring growth model using exact age as loadings
Mint Mslp | mon12-mon18 AT age12-age18;
Mint* Mslp* (Mintvar Mslpvar); ! M Int and slope variances
Mint WITH Mslp* (MIntSlp); ! M Int-slope covariance
[Mint* Mslp*]; ! M fixed growth effects
[mon12-mon18@0]; ! M Intercepts fixed to 0
mon12-mon18* (Mresvar); ! M Residual var held equal

! Regressions between outcomes
Rint ON Mint* (IntCont); ! Intercept contextual effect
Rslp ON Mslp* (SlpCont); ! Slope contextual effect
Rslp ON Mint* (Int2Slp); ! M int --> R slope between effect
Rint ON Mslp* (Slp2Int); ! M slope --> R int between effect
! Residual WP effect between same ages, held equal across age
risky12-risky18 PON mon12-mon18* (ResEff);

MODEL CONSTRAINT:
NEW(IntEff SlpEff ResStd IntStd SlpStd RIScor MIScor I2Sstd S2Istd);
IntEff = ResEff + IntCont; ! Between intercept effect
SlpEff = ResEff + SlpCont; ! Between slope effect

ResStd = ResEff * SQRT(Mresvar)/SQRT(Rresvar); ! STD WP effect
IntStd = IntEff * SQRT(Mintvar)/SQRT(Rintvar); ! STD Int effect
SlpStd = SlpEff * SQRT(Mslpvar)/SQRT(Rslpvar); ! STD Slope effect
I2Sstd = Int2Slp * SQRT(Mintvar)/SQRT(Rslpvar); ! STD M int --> R slope
S2Istd = Slp2Int * SQRT(Mslpvar)/SQRT(Rintvar); ! STD M slope --> R int
RIScor = RIntSlp / (SQRT(Rintvar)*SQRT(Rslpvar)); ! R Int-slope correlation
MIScor = MIntSlp / (SQRT(Mintvar)*SQRT(Mslpvar)); ! M Int-slope correlation
  
```

Here is my “latent growth curve structural equation model” using directed paths from monitoring to risky behavior. Can you spot the differences?



-> Indicates paths fixed = 1
- > Indicates paths fixed = time values
- ←-----> Indicates paths freely estimated
- > Indicates paths freely estimated
- > Indicates paths freely estimated between residuals at the same occasion but held equal over time

Mplus results for directed path SEM:

MODEL FIT INFORMATION						Means				
Number of Free Parameters				20		RQUAD	0.147	0.021	7.117	0.000
Loglikelihood						MINT	0.065	0.034	1.906	0.057
H0 Value				-4392.253		MSLP	-0.003	0.008	-0.402	0.688
Information Criteria						Intercepts				
Akaike (AIC)				8824.506		MON12	0.000	0.000	999.000	999.000
Bayesian (BIC)				8890.472		MON13	0.000	0.000	999.000	999.000
Sample-Size Adjusted BIC				8827.110		MON14	0.000	0.000	999.000	999.000
(n* = (n + 2) / 24)						MON15	0.000	0.000	999.000	999.000
MODEL RESULTS						MON16	0.000	0.000	999.000	999.000
		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	MON17	0.000	0.000	999.000	999.000
RINT	ON					MON18	0.000	0.000	999.000	999.000
MINT		-7.928	0.861	-9.211	0.000	RISKY12	0.000	0.000	999.000	999.000
MSLP		3.685	3.494	1.055	0.292	RISKY13	0.000	0.000	999.000	999.000
RSLP	ON					RISKY14	0.000	0.000	999.000	999.000
MSLP		-5.316	0.816	-6.517	0.000	RISKY15	0.000	0.000	999.000	999.000
MINT		-0.548	0.160	-3.431	0.001	RISKY16	0.000	0.000	999.000	999.000
RINT	ON					RISKY17	0.000	0.000	999.000	999.000
ATT4		-3.333	0.514	-6.491	0.000	RISKY18	0.000	0.000	999.000	999.000
RSLP	ON					RINT	23.610	0.333	70.898	0.000
ATT4		-0.530	0.103	-5.161	0.000	RSLP	2.004	0.139	14.405	0.000
RISKY12	ON					Variances				
MON12		3.559	0.301	11.809	0.000	RQUAD	0.000	0.000	999.000	999.000
RISKY13	ON					MINT	0.195	0.023	8.376	0.000
MON13		3.559	0.301	11.809	0.000	MSLP	0.010	0.001	7.803	0.000
RISKY14	ON					Residual Variances				
MON14		3.559	0.301	11.809	0.000	MON12	0.081	0.004	22.354	0.000
RISKY15	ON					MON13	0.081	0.004	22.354	0.000
MON15		3.559	0.301	11.809	0.000	MON14	0.081	0.004	22.354	0.000
RISKY16	ON					MON15	0.081	0.004	22.354	0.000
MON16		3.559	0.301	11.809	0.000	MON16	0.081	0.004	22.354	0.000
RISKY17	ON					MON17	0.081	0.004	22.354	0.000
MON17		3.559	0.301	11.809	0.000	MON18	0.081	0.004	22.354	0.000
RISKY18	ON					RISKY12	7.329	0.328	22.353	0.000
MON18		3.559	0.301	11.809	0.000	RISKY13	7.329	0.328	22.353	0.000
RINT	WITH					RISKY14	7.329	0.328	22.353	0.000
RSLP		1.481	0.345	4.291	0.000	RISKY15	7.329	0.328	22.353	0.000
MINT	WITH					RISKY16	7.329	0.328	22.353	0.000
MSLP		0.000	0.004	-0.118	0.906	RISKY17	7.329	0.328	22.353	0.000
						RISKY18	7.329	0.328	22.353	0.000
						RINT	14.173	1.965	7.213	0.000
						RSLP	0.394	0.082	4.787	0.000
						New/Additional Parameters				
						INTEFF	-4.369	0.784	-5.575	0.000
						SLPEFF	-1.758	0.724	-2.429	0.015
						RESSTD	0.374	0.034	11.063	0.000
						INTSTD	-0.513	0.104	-4.928	0.000
						SLPSTD	-0.287	0.126	-2.270	0.023
						RISCOR	0.627	0.068	9.266	0.000
						MISCOR	-0.010	0.089	-0.117	0.907
						I2SSTD	-0.386	0.125	-3.078	0.002
						S2ISTD	0.100	0.095	1.051	0.293

In Mplus still, doing the same thing as a “truly multivariate” MLM instead of SEM (Model #5)
This is called “multilevel SEM” by some people...

```

TITLE: Multivariate Growth Model as MLM with directed paths
DATA: FILE = chapter9v3.csv; ! Syntax in same folder as data
VARIABLE:
! List of variables in data file
  NAMES = FamilyID occasion age monitor risky age18 att4
          PMmon3 WPmon Age18M3 C18Mon agesq mon3;
! Variables to be analyzed in this model
  USEVARIABLE = age18 agesq att4 risky mon3;
  MISSING ARE ALL (-999); ! Missing data identifier
! MLM options
  CLUSTER = FamilyID; ! Level-2 ID
  BETWEEN = att4; ! Observed ONLY level-2 predictors
  WITHIN = age18 agesq; ! Observed ONLY level-1 predictors

ANALYSIS: TYPE = TWOLEVEL RANDOM; ESTIMATOR = ML;
MODEL: ! R = risky behavior, M = monitoring
%WITHIN%
  risky* mon3* (Rresvar Mresvar); ! Residual variances
  Rslp | risky ON age18*; ! R linear age slope
  Rquad | risky ON agesq*; ! R quadratic age slope
  Mslp | mon3 ON age18*; ! M linear age slope
  WPres | risky ON mon3*; ! WP effect M --> R

%BETWEEN%
  risky* mon3* (Rintvar Mintvar); ! Intercept variances
  Rslp* Mslp* (Rslpvar Mslpvar); ! Linear age slope variances
  Rquad@0; ! No quadratic age slope variance
  [risky* mon3*]; ! Fixed intercepts
  [Rslp* Rquad* Mslp*]; ! Fixed age slopes
  risky Rslp ON att4*; ! Att --> R int, linear age slope
  risky WITH Rslp* (RIntSlp); ! R Int-slope covariance
  mon3 WITH Mslp* (MIntSlp); ! M Int-slope covariance

! Regressions between outcomes
  risky ON mon3* (IntCont); ! Intercept contextual effect
  Rslp ON Mslp* (SlpCont); ! Slope contextual effect
  Rslp ON mon3* (Int2Slp); ! M int --> R slope between effect
  risky ON Mslp* (Slp2Int); ! M slope --> R int between effect

! Residual WP effect between same ages, held equal across age
  [WPres] (ResEff);
  WPres@0; ! No random WP effect variance

MODEL CONSTRAINT:
NEW(IntEff SlpEff ResStd IntStd SlpStd RIScor MIScor I2Sstd S2Istd);

IntEff = ResEff + IntCont; ! Between intercept effect
SlpEff = ResEff + SlpCont; ! Between slope effect

ResStd = ResEff * SQRT(Mresvar)/SQRT(Rresvar); ! STD WP effect
IntStd = IntEff * SQRT(Mintvar)/SQRT(Rintvar); ! STD Int effect
SlpStd = SlpEff * SQRT(Mslpvar)/SQRT(Rslpvar); ! STD Slope effect

I2Sstd = Int2Slp * SQRT(Mintvar)/SQRT(Rslpvar); ! STD M int --> R slope
S2Istd = Slp2Int * SQRT(Mslpvar)/SQRT(Rintvar); ! STD M slope --> R int

RIScor = RIntSlp / (SQRT(Rintvar)*SQRT(Rslpvar)); ! R Int-slope correlation
MIScor = MIntSlp / (SQRT(Mintvar)*SQRT(Mslpvar)); ! M Int-slope correlation

```

From chapter 9:

Figure 9.5. Multivariate longitudinal model when using truly multivariate software.

Level 1: $\text{Monitor}_{ti} - 3 = \beta_{00M} + \beta_{10M} (\text{Age}_{tiM} - 18) + e_{tiM}$

$$\text{Risky}_{ti} = \beta_{00R} + \beta_{10R} (\text{Age}_{tiR} - 18) + \beta_{20R} (\text{Age}_{tiR} - 18)^2 + \beta_{30R} (e_{tiM}) + e_{tiR}$$

Level 2:

Monitor Intercept: $\beta_{00M} = \gamma_{00M} + U_{0iM}$

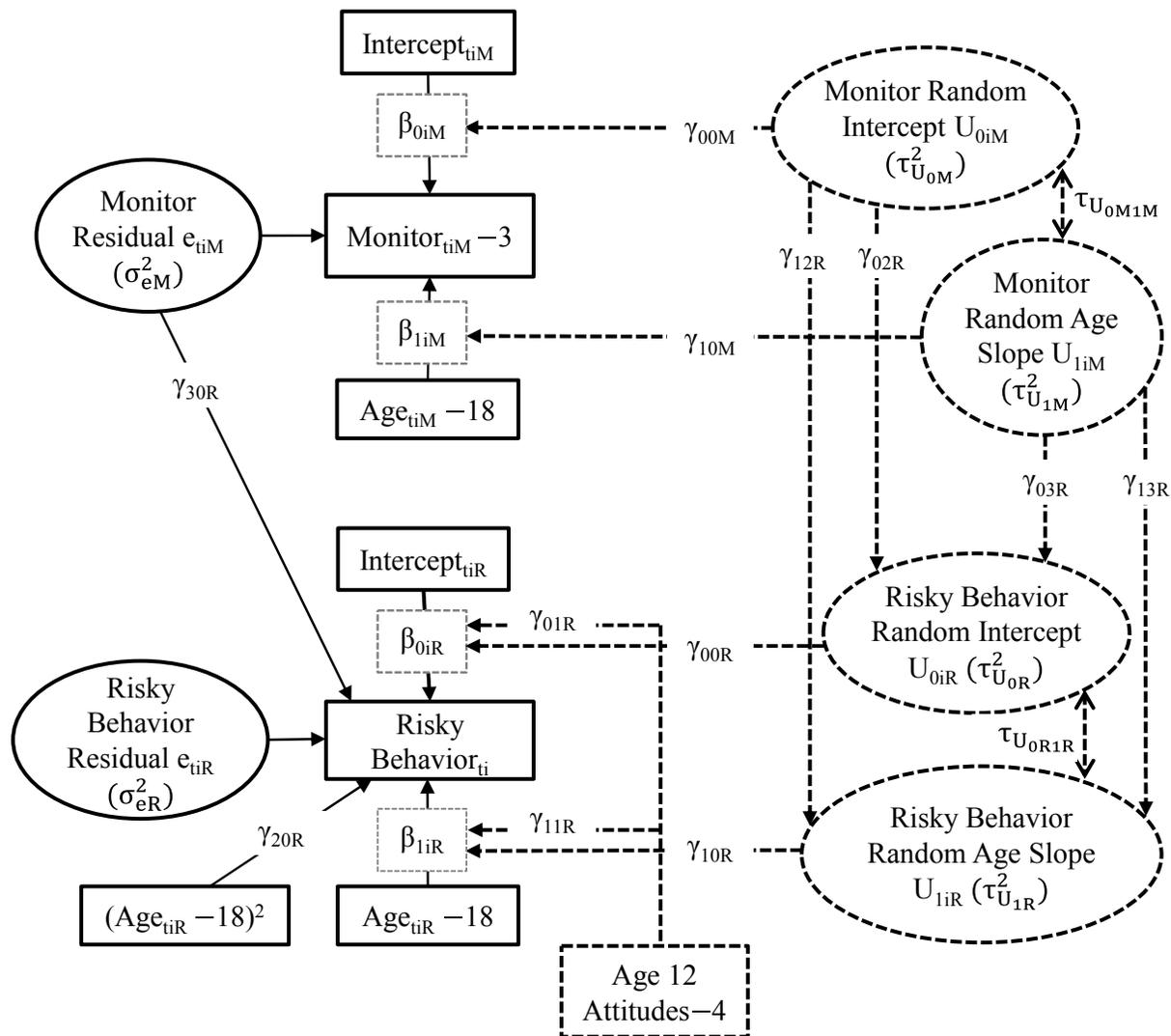
Monitor Age: $\beta_{10M} = \gamma_{10M} + U_{1iM}$

Risky Intercept: $\beta_{00R} = \gamma_{00R} + \gamma_{01R} (\text{Age12Attitudes}_i - 4) + \gamma_{02R} (U_{0iM}) + \gamma_{03R} (U_{1iM}) + U_{0iR}$

Risky Age: $\beta_{10R} = \gamma_{10R} + \gamma_{11R} (\text{Age12Attitudes}_i - 4) + \gamma_{12R} (U_{0iM}) + \gamma_{13R} (U_{1iM}) + U_{1iR}$

Risky Age²: $\beta_{20R} = \gamma_{20R}$

Risky WP Monitor: $\beta_{30R} = \gamma_{30R}$



From chapter 9:

Table 9.5. Results from multivariate longitudinal model using truly multivariate software.

Model Effects		Est	SE	<i>p</i> <	STD
<u>Risky Behavior Model for the Means</u>					
γ_{00R}	Intercept	23.61	0.33	.001	
γ_{10R}	Linear Age Slope (0 = 18)	2.00	0.14	.001	
γ_{20R}	Quadratic Age Slope	0.15	0.02	.001	
γ_{01R}	Mothers' Attitudes (0 = 4)	-3.33	0.51	.001	
γ_{11R}	Attitudes by Linear Age	-0.53	0.10	.001	
<u>Monitoring Model for the Means</u>					
γ_{00M}	Intercept	0.07	0.03	.057	
γ_{10M}	Linear Age Slope (0 = 18)	-0.00	0.01	.704	
<u>Risky Behavior Model for the Variance</u>					
$\tau_{U_{0R}}^2$	Random Intercept Variance	14.17	1.97	.001	
$\tau_{U_{1R}}^2$	Linear Age Slope Variance	0.39	0.08	.001	
$\tau_{U_{0R1R}}$	Intercept-Age Slope Covariance	1.48	0.35	.001	
σ_{eR}^2	Residual Variance	7.33	0.33	.001	
<u>Monitoring Model for the Variance</u>					
$\tau_{U_{0M}}^2$	Random Intercept Variance	0.20	0.02	.001	
$\tau_{U_{1M}}^2$	Linear Age Slope Variance	0.01	0.00	.001	
$\tau_{U_{0M1M}}$	Intercept-Age Slope Covariance	-0.00	0.00	.916	
σ_{eM}^2	Residual Variance	0.08	0.00	.001	
<u>Cross-Variable Regressions</u>					
Monitoring Intercept →					
Risky Behavior Intercept					
γ_{02R}	Contextual Effect	-7.93	0.86	.001	
$\gamma_{02R} + \gamma_{30R}$	Total Effect	-4.37	0.78	.001	-0.51
Monitoring Age Slope →					
Risky Behavior Age Slope					
γ_{13R}	Contextual Effect	-5.32	0.82	.001	
$\gamma_{13R} + \gamma_{30R}$	Total Effect	-1.76	0.72	.015	-0.29
Monitoring Residual →					
Risky Behavior Residual					
γ_{30R}		3.56	0.30	.001	0.37
Monitoring Intercept →					
Risky Behavior Age Slope					
γ_{12R}		-0.55	0.16	.001	-0.39
Monitoring Age Slope →					
Risky Behavior Intercept					
γ_{03R}		3.69	3.49	.291	0.10

What Mplus actually gave me for my “truly multivariate” MLM that I used to make Table 9.5:

```

MODEL FIT INFORMATION
Number of Free Parameters                20

Loglikelihood
  H0 Value                               -4392.253
Information Criteria
  Akaike (AIC)                           8824.506
  Bayesian (BIC)                          8929.390
  Sample-Size Adjusted BIC                8865.858
  (n* = (n + 2) / 24)

MODEL RESULTS

                Estimate      S.E.  Est./S.E.  Two-Tailed
                P-Value

Within Level

Residual Variances
  MON3          0.081      0.004    22.355    0.000
  RISKY         7.329      0.328    22.353    0.000

Between Level

RSLP      ON
  MSLP          -5.316      0.816    -6.517    0.000

RSLP      ON
  ATT4          -0.530      0.103    -5.161    0.000
  MON3          -0.548      0.160    -3.431    0.001

RISKY     ON
  MSLP          3.685      3.494     1.055    0.292

RISKY     ON
  ATT4          -3.333      0.514    -6.491    0.000
  MON3          -7.928      0.861    -9.211    0.000

RISKY     WITH
  RSLP          1.481      0.345     4.291    0.000

MON3      WITH
  MSLP          0.000      0.004    -0.118    0.906

Means
  MON3          0.065      0.034     1.906    0.057
  RQUAD         0.147      0.021     7.117    0.000
  MSLP         -0.003      0.008    -0.402    0.688
  WPRES         3.559      0.301    11.810    0.000

Intercepts
  RISKY         23.610      0.333    70.898    0.000
  RSLP          2.004      0.139    14.405    0.000

Variances
  MON3          0.195      0.023     8.376    0.000
  RQUAD         0.000      0.000    999.000    999.000
  MSLP          0.010      0.001     7.803    0.000
  WPRES         0.000      0.000    999.000    999.000

Residual Variances
  RISKY         14.173      1.965     7.213    0.000
  RSLP          0.394      0.082     4.787    0.000

New/Additional Parameters
  INTEFF        -4.369      0.784    -5.574    0.000
  SLPEFF        -1.758      0.724    -2.428    0.015
  RESSTD         0.374      0.034    11.063    0.000
  INTSTD        -0.513      0.104    -4.928    0.000
  SLPSTD        -0.287      0.126    -2.269    0.023
  RISCOR         0.627      0.068     9.266    0.000
  MISCOR        -0.010      0.089    -0.117    0.907
  I2SSTD        -0.386      0.125    -3.078    0.002
  S2ISTD         0.100      0.095     1.051    0.293

```

In SAS NL MIXED, where (currently) I can get everything except the residual directed path ☹️ (#6)

```

TITLE1 "Truly Multivariate Model (but without residual path)";
PROC NL MIXED DATA=RiskyStacked2 METHOD=GAUSS TECH=QUANEW GCONV=1e-12;
* Starting values for all fixed effects and variance components;
  PARSMS FintR=23 FslpR=2 Fslp2R=.15 FattintR=-3 FattslpR=-.5 FintM=0 FslpM=0
    FintMintR=-4 FintMslpR=-.5 FslpMintR=3.7 FslpMslpR=-1.7
    ResVarR=7 IntVarR=14 SlpVarR=.4 CovarR=1.5 ResVarM=.1 IntVarM=.2 SlpVarM=.01 CovarM=0;
* Dont allow variances to go below 0 during estimation;
  BOUNDS ResVarR>0, IntVarR>0, slpVarR>0, ResVarM>0, IntVarM>0, slpVarM>0;
* Level-2 model;
  B0M = FintM + U0M;
  B1M = FslpM + U1M;
  B0R = FintR + FattintR*att4 + FintMintR*U0M + FslpMintR*U1M + U0R;
  B1R = FslpR + FattslpR*att4 + FintMslpR*U0M + FslpMslpR*U1M + U1R;
* Level-1 model;
  predY = dvM*(B0M + B1M*agec18) + dvR*(B0R + B1R*agec18 + Fslp2R*agec18*agec18);
  ResVar = dvR*ResVarR + dvM*ResVarM;
* Put models back together;
  MODEL outcome ~ NORMAL(predY, ResVar);
* Define G matrix;
  RANDOM U0R U1R U0M U1M ~ NORMAL([0,0,0,0],[IntVarR,
    CovarR, slpVarR,
    0, 0, IntVarM,
    0, 0, CovarM, slpVarM]) SUBJECT=FamilyID;
* Estimating standardized effects;
  ESTIMATE "STD M --> R Intercept" FintMintR*SQRT(IntVarM)/SQRT(IntVarR);
  ESTIMATE "STD M --> R Slope" FslpMslpR*SQRT(SlpVarM)/SQRT(SlpVarR);
  ESTIMATE "STD M Int --> R Slope" FintMslpR*SQRT(IntVarM)/SQRT(SlpVarR);
  ESTIMATE "STD M Slope --> R Int" FslpMintR*SQRT(SlpVarM)/SQRT(IntVarR);
RUN;

```

Fit Statistics

-2 Log Likelihood	8915.1
AIC (smaller is better)	8953.1
AICC (smaller is better)	8953.4
BIC (smaller is better)	9015.8

Parameter Estimates

Parameter	Estimate	Standard Error	DF	t Value	Pr > t	Alpha	Lower	Upper	Gradient
FintR	23.3053	0.3499	196	66.60	<.0001	0.05	22.6152	23.9954	-0.00005
FslpR	1.9658	0.1460	196	13.46	<.0001	0.05	1.6778	2.2537	0.000057
Fslp2R	0.1452	0.02196	196	6.61	<.0001	0.05	0.1019	0.1886	-0.00034
FattintR	-3.3299	0.5138	196	-6.48	<.0001	0.05	-4.3431	-2.3166	-0.00002
FattslpR	-0.5285	0.1027	196	-5.15	<.0001	0.05	-0.7311	-0.3260	0.000042
FintM	0.06501	0.03413	196	1.91	0.0582	0.05	-0.00229	0.1323	0.000303
FslpM	-0.00330	0.008178	196	-0.40	0.6866	0.05	-0.01943	0.01282	-0.00017
FintMintR	-3.6741	0.7651	196	-4.80	<.0001	0.05	-5.1831	-2.1651	0.000013
FintMslpR	-0.3891	0.1531	196	-2.54	0.0118	0.05	-0.6910	-0.08715	-0.00003
FslpMintR	6.7128	3.4138	196	1.97	0.0507	0.05	-0.01980	13.4454	6.237E-6
FslpMslpR	-0.7625	0.6843	196	-1.11	0.2665	0.05	-2.1121	0.5871	-0.00002
ResVarR	8.3529	0.3736	196	22.36	<.0001	0.05	7.6162	9.0897	0.000018
IntVarR	14.9515	1.9144	196	7.81	<.0001	0.05	11.1761	18.7270	0.000021
SlpVarR	0.4529	0.07760	196	5.84	<.0001	0.05	0.2998	0.6059	0.000043
CovarR	1.6595	0.3295	196	5.04	<.0001	0.05	1.0097	2.3093	-0.00004
ResVarM	0.08076	0.003612	196	22.36	<.0001	0.05	0.07363	0.08788	0.000718
IntVarM	0.1954	0.02333	196	8.38	<.0001	0.05	0.1494	0.2414	-0.0002
SlpVarM	0.01049	0.001344	196	7.80	<.0001	0.05	0.007838	0.01314	0.001201
CovarM	-0.00044	0.004007	196	-0.11	0.9122	0.05	-0.00834	0.007460	-0.0019

Additional Estimates → close, but not close enough ☹️

Label	Estimate	Standard Error	DF	t Value	Pr > t	Alpha	Lower	Upper
STD M --> R Intercept	-0.4200	0.09494	196	-4.42	<.0001	0.05	-0.6073	-0.2328
STD M --> R Slope	-0.1160	0.1051	196	-1.10	0.2707	0.05	-0.3232	0.09113
STD M Int --> R Slope	-0.2556	0.1045	196	-2.45	0.0153	0.05	-0.4616	-0.04954
STD M Slope --> R Int	0.1778	0.09184	196	1.94	0.0543	0.05	-0.00332	0.3589

What if your truly multivariate model won't estimate? Here is an observed variable alternative using SAS PROC MIXED to output per-person random effects and residuals (#7; "slopes-as-outcomes")

```
TITLE1 "Random Linear Age Model for Parent Monitoring to Output Random Effects and Residuals";
PROC MIXED DATA=RiskyStacked NOITPRINT NOCLPRINT COVTEST IC NAMELEN=100 METHOD=ML;
  CLASS FamilyID occasion;
  MODEL monitor = agec18 / SOLUTION DDFM=Satterthwaite NOTEST OUTP=eUformonitor;
  RANDOM INTERCEPT agec18 / SOLUTION TYPE=UN SUBJECT=FamilyID; * Add solution;
  ODS OUTPUT SolutionR=Uformonitor; * Save random effects to dataset;
RUN; TITLE1;
```

New "Uformonitor" random effects dataset:

	Effect	FamilyID	Estimate	StdErrPred	DF	tValue	Probt
1	Intercept	1	-0.2618	0.1669	924	-1.57	0.1170
2	agec18	1	0.03944	0.04549	843	0.87	0.3861
3	Intercept	2	0.4919	0.1717	889	2.86	0.0043
4	agec18	2	-0.08408	0.04531	823	-1.86	0.0639

```
* Save random intercept centered at 3 to new dataset (have to add fixed effect);
DATA Uint; SET Uformonitor; WHERE INDEX(Effect,"Intercept")>0;
  Uint=Estimate+3.0650-3; KEEP FamilyID Uint; RUN;
```

```
* Save random slope to new dataset uncentered since fixed effect is near 0;
DATA Uage; SET Uformonitor; WHERE INDEX(Effect,"agec18")>0;
  Uage=Estimate; KEEP FamilyID Uage; RUN;
```

```
* Save residuals to new dataset;
DATA eUage; SET eUformonitor;
  Eres=Resid; KEEP FamilyID occasion Eres; RUN;
```

```
* Merge back into original data;
DATA RiskyStacked; MERGE RiskyStacked Uint Uage; BY FamilyID; RUN;
DATA RiskyStacked; MERGE RiskyStacked eUage; BY FamilyID occasion; RUN;
```

Slopes-as-outcomes for time-varying monitoring predicting risky behavior:

$$\text{Level 1: Risky Behavior}_{ti} = \beta_{0i} + \beta_{1i}(\text{Age}_{ti} - 18) + \beta_{2i}(\text{Age}_{ti} - 18)^2 + \beta_{3i}(\text{Mon Res}_{ti}) + e_{ti}$$

$$\text{Level 2: Intercept: } \beta_{0i} = \gamma_{00} + \gamma_{01}(\text{Attitudes12}_i - 4) \\ + \gamma_{02}(\text{MonInt}_i - 3) + \gamma_{03}(\text{MonSlope}_i) + U_{0i}$$

$$\text{Age: } \beta_{1i} = \gamma_{10} + \gamma_{11}(\text{Attitudes12}_i - 4) \\ + \gamma_{12}(\text{MonInt}_i - 3) + \gamma_{13}(\text{MonSlope}_i) + U_{1i}$$

$$\text{Age}^2: \beta_{2i} = \gamma_{20}$$

$$\text{WP Monitor: } \beta_{3i} = \gamma_{30}$$

Composite :

$$y_{ti} = \left[\gamma_{00} + \gamma_{01}(\text{Attitudes12}_i - 4) + \gamma_{02}(\text{MonInt}_i - 3) + \gamma_{03}(\text{MonSlope}_i) + U_{0i} \right] + \\ \left[\gamma_{10} + \gamma_{11}(\text{Attitudes12}_i - 4) + \gamma_{12}(\text{MonInt}_i - 3) + \gamma_{13}(\text{MonSlope}_i) + U_{1i} \right] (\text{Age}_{ti} - 18) + \\ \left[\gamma_{20} \right] (\text{Age}_{ti} - 18)^2 + \left[\gamma_{30} \right] (\text{Mon Res}_{ti}) + e_{ti}$$

```
TITLE1 "Monitoring Us predicting risky behavior";
PROC MIXED DATA=RiskyStacked NOITPRINT NOCLPRINT COVTEST IC NOINFO NAMELEN=100 METHOD=ML;
  CLASS FamilyID occasion;
  MODEL risky = agec18 agec18*agec18 att4 att4*agec18 Uint Uint*agec18 Uage Uage*agec18 Eres
    / SOLUTION DDFM=Satterthwaite NOTEST;
  RANDOM INTERCEPT agec18 / TYPE=UN SUBJECT=FamilyID;
  ODS OUTPUT InfoCrit=FixedU; RUN; TITLE1;
```

Covariance Parameter Estimates						
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z	
UN(1,1)	FamilyID	15.5934	1.9076	8.17	<.0001	
UN(2,1)	FamilyID	1.7982	0.3275	5.49	<.0001	
UN(2,2)	FamilyID	0.4981	0.07694	6.47	<.0001	
Residual		7.3316	0.3279	22.36	<.0001	

Information Criteria						
Neg2LogLike	Parms	AIC	AICC	HQIC	BIC	CAIC
7430.8	14	7458.8	7459.1	7477.5	7505.0	7519.0

Solution for Fixed Effects						
Effect	Estimate	Standard Error	DF	t Value	Pr > t	
Intercept	23.5971	0.3295	244	71.62	<.0001	
agec18	2.0098	0.1384	1186	14.52	<.0001	
agec18*agec18	0.1465	0.02058	1010	7.12	<.0001	
att4	-3.3318	0.5137	200	-6.49	<.0001	
agec18*att4	-0.5294	0.1027	199	-5.15	<.0001	
Uint	-4.3591	0.7652	202	-5.70	<.0001	
agec18*Uint	-0.5475	0.1530	201	-3.58	0.0004	
Uage	3.7561	3.4127	202	1.10	0.2724	
agec18*Uage	-1.7481	0.6858	206	-2.55	0.0115	
Eres	3.5580	0.3013	1000	11.81	<.0001	

So how did we do? The variances of the monitoring predictors from the slopes-as-outcomes model are smaller (shrunken) as expected. Although this may not always be the case, here the results do appear similar, even though the effect sizes are slightly smaller for the slopes-as-outcomes model.

Table 9.7. Comparison of results for the intercepts (int), age slopes (slope), and residuals (res) for monitoring (M) predicting risky behavior (RB) across models. Bold values are $p < .05$ for the unstandardized fixed effects.

Monitoring Effects	Multivariate Longitudinal Model with Fixed Effects of Monitoring				Slopes-as-Outcomes Model: Persons as Random Effects			
	Var(X)	Var(Y)	Fixed Effect	STD Effect	Var(X)	Var(Y)	Fixed Effect	STD Effect
M int →								
R int	0.195	14.17	-4.37	-0.51	0.168	15.59	-4.36	-0.45
M int →								
R slope	0.195	0.39	-0.55	-0.39	0.168	0.50	-0.55	-0.32
M slope →								
R int	0.010	14.17	3.69	0.10	0.008	15.59	3.76	0.09
M slope →								
R slope	0.010	0.39	-1.76	-0.29	0.008	0.50	-1.75	-0.23
M res →								
R res	0.081	7.33	3.56	0.37	0.062	7.33	3.56	0.33

Ok, so this brings up more questions... is the slopes-as-outcomes model still reasonably ok if we add additional effects? For example, what about a WP*age interaction or a random WP effect?

Adding a WP*age interaction using Slopes-as-Outcomes in PROC MIXED:

```
TITLE1 "Monitoring Us predicting risky behavior with WP*age interaction";
PROC MIXED DATA=RiskyStacked NOITPRINT NOCLPRINT COVTEST IC NOINFO NAMELEN=100 METHOD=ML;
  CLASS FamilyID occasion;
  MODEL risky = agec18 agec18*agec18 att4 att4*agec18 Uint Uint*agec18 Uage Uage*agec18
    Eres Eres*agec18 / SOLUTION DDFM=Satterthwaite NOTEST;
  RANDOM INTERCEPT agec18 / TYPE=UN SUBJECT=FamilyID; RUN; TITLE1;
```

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > t
Eres	5.2010	0.6071	1095	8.57	<.0001
agec18*Eres	0.5445	0.1749	1122	3.11	0.0019

Adding a WP*age interaction in the Directed Path version of SEM in Mplus:

```
MODEL CONSTRAINT: ! ResLin = linear change in WP effect across age
NEW(ResLin);
```

```
ResLin = ResEff13 - ResEff12;
ResLin = ResEff14 - ResEff13;
ResLin = ResEff15 - ResEff14;
ResLin = ResEff16 - ResEff15;
ResLin = ResEff17 - ResEff16;
ResLin = ResEff18 - ResEff17;
```

```
! Residual WP effect between same ages, now differs by age
risky12-risky18 PON mon12-mon18* (ResEff12-ResEff18);
```

NEW PARMS	EST	SE	Z	p-value
RESLIN	0.151	0.129	1.177	0.239

Adding a WP*age interaction in the Directed Path version of MLM in Mplus:

```
DEFINE: agemon3 = age18*mon3; ! Make observed variable interaction term to use as predictor;
```

```
%WITHIN% ! WP*age effect
WPage | risky ON agemon3*;
```

Means	EST	SE	Z	p-value
WPAGE	0.171	0.131	1.303	0.193

```
%BETWEEN% ! Fixed WP*age effect only
[WPage*]; WPage@0;
```

What about adding a random WP effect using Slopes-as-Outcomes in PROC MIXED:

```
TITLE1 "Monitoring Us predicting risky behavior with random WP effect";
PROC MIXED DATA=RiskyStacked NOITPRINT NOCLPRINT COVTEST IC NOINFO NAMELEN=100 METHOD=ML;
  CLASS FamilyID occasion;
  MODEL risky = agec18 agec18*agec18 att4 att4*agec18 Uint Uint*agec18 Uage Uage*agec18
    Eres / SOLUTION DDFM=Satterthwaite NOTEST OUTPM=PredUmon;
  RANDOM INTERCEPT agec18 Eres / TYPE=UN SUBJECT=FamilyID;
  ODS OUTPUT InfoCrit=RandomU; RUN; TITLE1; %FitTest(FitFewer=FixedU, FitMore=RandomU);
```

Likelihood Ratio Test for FixedU vs. RandomU

Name	Like	Parms	AIC	BIC	DevDiff	DFdiff	Pvalue
FixedU	7430.8	14	7458.8	7505.0	.	.	.
RandomU	7420.5	17	7454.5	7510.6	10.3083	3	0.016120

Adding a random WP effect in the Directed Path version of MLM in Mplus (not available in SEM):

```
%BETWEEN%
WPres*; WPres WITH risky* mon3* Rslp* Mslp*; ! Random WP effect variance and covariances added
```

Likelihood Ratio Test for Random Effect in Multivariate Model in Mplus:

Name	LL	Parms	AIC	BIC	-2ΔLL	DFdiff	Pvalue
FixedU	-4392.3	20	8824.5	8929.4	.	.	.
RandomU	-4389.2	25	8828.4	8959.5	4.67	5	0.46

Uh-oh... it looks like the slopes-as-outcomes model may paint too rosy of a picture by treating estimated quantities (random effects and residuals) as perfectly reliable observed variables...
...so try to use a multivariate model whenever you can, and proceed with caution otherwise...