

## Latent Growth Curve with Time-invariant Covariate

```
title: Latent growth curve example (health.dat is data from LSEM Ch 7);

data: file=health.dat; format=free;

variable:
  names=
  age
  srh1 srh2 srh3 srh4 srh5 srh6
  bmi1 bmi2 bmi3 bmi4 bmi5 bmi6
  cesdna1 cesdpa1 cesdso1
  cesdna2 cesdpa2 cesdso2
  cesdna3 cesdpa3 cesdso3
  cesdna4 cesdpa4 cesdso4
  cesdna5 cesdpa5 cesdso5
  cesdna6 cesdpa6 cesdso6
  diab1 diab2 diab3 diab4 diab5 diab6;

usevariables=
  srh1 cesd1 cesd2 cesd3 cesd4 cesd5 cesd6;

define:
  cesd1 = mean (cesdna1 cesdpa1 cesdso1);
  cesd2 = mean (cesdna2 cesdpa2 cesdso2);
  cesd3 = mean (cesdna3 cesdpa3 cesdso3);
  cesd4 = mean (cesdna4 cesdpa4 cesdso4);
  cesd5 = mean (cesdna5 cesdpa5 cesdso5);
  cesd6 = mean (cesdna6 cesdpa6 cesdso6);
  center srh1(grandmean);

analysis: type=general; estimator=mlm;
model:
  i by cesd1@1 cesd2@1 cesd3@1 cesd4@1 cesd5@1 cesd6@1;
  s by cesd1@0 cesd2@1 cesd3@2 cesd4@3 cesd5@4 cesd6@5;
  i s;
  i on srh1;
  s on srh1 (b3);
  srh1 (srh);
  i with s;
  [i] (b2);
  [s] (b1);
  [cesd1-cesd6@0];

!SIMPLE SLOPES COMPUTATIONS;
model constraint:
  ! srh mean is 3.521 obtained from prior analysis (var=1.217, SD=1.103);

  !declare new names for W values and simple slopes;
  NEW(LOW_W MED_W HIGH_W SIMP_LO SIMP_MED SIMP_HI);

  !simple slope equations;
  LOW_W = 3.521 - 1*(sqrt(srh)) ; !-1 SD below mean of W;
  MED_W = 3.521 ; ! mean of W;
  HIGH_W = 3.521 + 1*(sqrt(srh)); ! +1 SD below mean of W;

  ! Now calc simple slopes for each value of W;
  SIMP_LO = b1 + b3*LOW_W;
  SIMP_MED = b1 + b3*MED_W;
  SIMP_HI = b1 + b3*HIGH_W;

  ! Use loop plot to plot slopes of X on Y for low, med, high values of W
  ! NOTE - values from -3 to 3 in LOOP() statement since
  ! X is factor with mean set at default of 0
  !From user guide on loop function: "The LOOP option names
  !the variable that will be plotted on the x-axis, gives
  !the numbers that are the lower and upper values of the variable, and the
  !incremental value of the variable to be used in the computations;
  PLOT(LOMOD MEDMOD HIMOD);
  LOOP(XVAL,1,6,1);
  LOMOD = (b1 + b3*LOW_W)*XVAL;
  MEDMOD = (b1 + b3*MED_W)*XVAL;
  HIMOD = (b1 + b3*HIGH_W)*XVAL;

PLOT:
```

TYPE = plot2;

output: sampstat stdyx;

INPUT READING TERMINATED NORMALLY

Latent growth curve example (health.dat is data from LSEM Ch 7);

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	5335

Estimator	MLM
Information matrix	EXPECTED

MODEL FIT INFORMATION

Number of Free Parameters	15
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Loglikelihood

H0 Value	-23588.057
H1 Value	-23444.915

Information Criteria

Akaike (AIC)	47206.114
Bayesian (BIC)	47304.845
Sample-Size Adjusted BIC	47257.180
(n* = (n + 2) / 24)	

Chi-Square Test of Model Fit

Value	286.781*
Degrees of Freedom	20
P-Value	0.0000
Scaling Correction Factor	0.9983
for MLM	

\* The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used for chi-square difference testing in the regular way. MLM, MLR and WLSM chi-square difference testing is described on the Mplus website. MLMV, WLSMV, and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.050
90 Percent C.I.	0.045 0.055
Probability RMSEA <= .05	0.488

CFI/TLI

CFI	0.980
TLI	0.979

Chi-Square Test of Model Fit for the Baseline Model

Value	13329.487
Degrees of Freedom	21
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value	0.031
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MODEL RESULTS

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
I	BY				
	CESD1	1.000	0.000	999.000	999.000
	CESD2	1.000	0.000	999.000	999.000
	CESD3	1.000	0.000	999.000	999.000
	CESD4	1.000	0.000	999.000	999.000
	CESD5	1.000	0.000	999.000	999.000
	CESD6	1.000	0.000	999.000	999.000
S	BY				
	CESD1	0.000	0.000	999.000	999.000
	CESD2	1.000	0.000	999.000	999.000
	CESD3	2.000	0.000	999.000	999.000
	CESD4	3.000	0.000	999.000	999.000
	CESD5	4.000	0.000	999.000	999.000
	CESD6	5.000	0.000	999.000	999.000
I	ON				
	SRH1	-0.166	0.005	-34.478	0.000
S	ON				
	SRH1	0.006	0.001	5.080	0.000
I	WITH				
	S	-0.003	0.001	-4.358	0.000
Means					
	SRH1	0.000	0.015	0.000	1.000
Intercepts					
	CESD1	0.000	0.000	999.000	999.000
	CESD2	0.000	0.000	999.000	999.000
	CESD3	0.000	0.000	999.000	999.000
	CESD4	0.000	0.000	999.000	999.000
	CESD5	0.000	0.000	999.000	999.000
	CESD6	0.000	0.000	999.000	999.000
	I	0.304	0.005	58.021	0.000
	S	0.004	0.001	3.249	0.001
Variances					
	SRH1	1.217	0.024	51.679	0.000
Residual Variances					
	CESD1	0.111	0.003	36.448	0.000
	CESD2	0.114	0.003	43.761	0.000
	CESD3	0.114	0.002	45.458	0.000
	CESD4	0.108	0.002	44.785	0.000
	CESD5	0.105	0.002	42.978	0.000
	CESD6	0.108	0.003	36.544	0.000
	I	0.089	0.003	29.296	0.000
	S	0.002	0.000	10.569	0.000
New/Additional Parameters					
	LOW_W	2.418	0.011	226.481	0.000
	MED_W	3.521	0.000	0.000	1.000
	HIGH_W	4.624	0.011	433.199	0.000
	SIMP_LO	0.018	0.003	6.009	0.000
	SIMP_MED	0.024	0.004	5.845	0.000
	SIMP_HI	0.030	0.005	5.712	0.000

STANDARDIZED MODEL RESULTS

STDYX Standardization

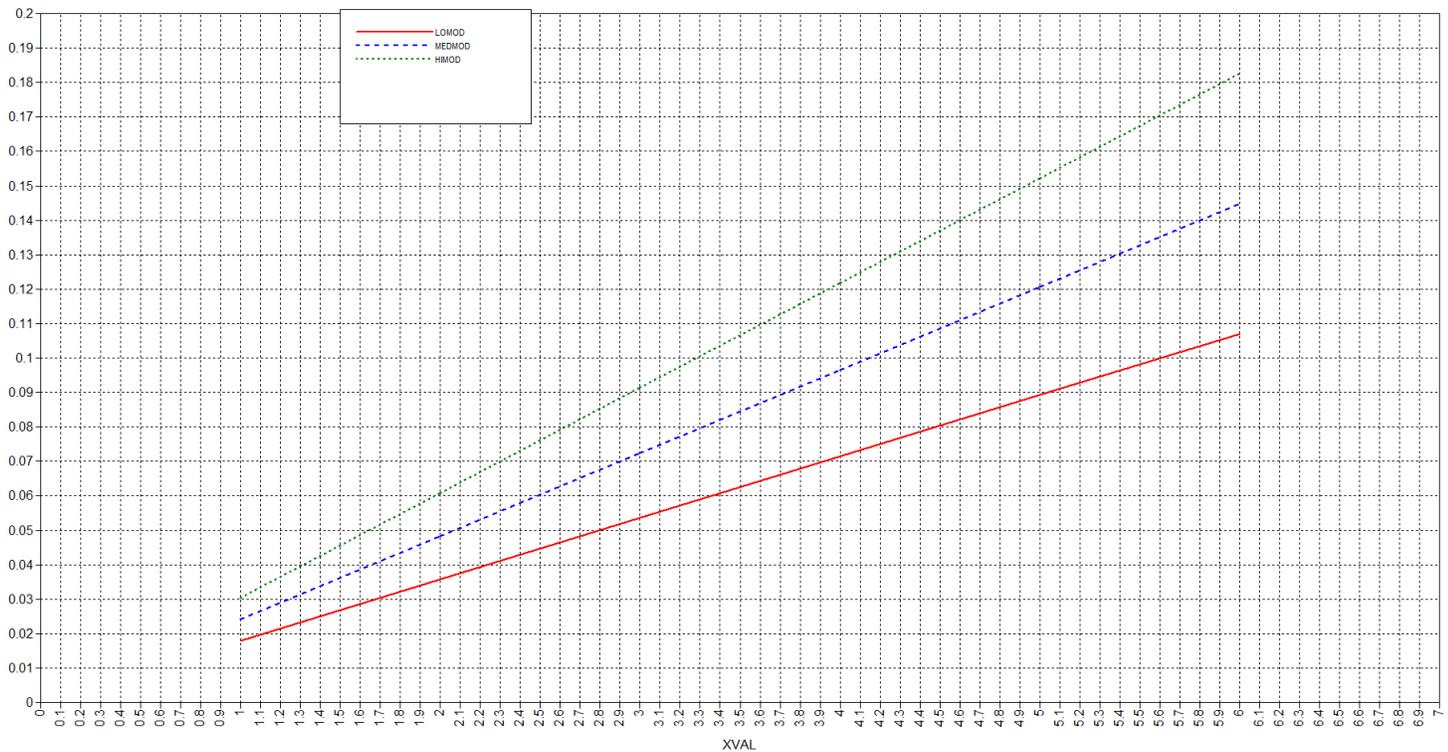
		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
I	BY				
	CESD1	0.725	0.008	92.287	0.000
	CESD2	0.728	0.008	89.372	0.000
	CESD3	0.732	0.009	82.520	0.000

CESD4		0.737	0.010	73.384	0.000
CESD5		0.731	0.011	67.353	0.000
CESD6		0.710	0.011	61.808	0.000
S	BY				
CESD1		0.000	0.000	999.000	999.000
CESD2		0.093	0.004	21.424	0.000
CESD3		0.188	0.009	21.419	0.000
CESD4		0.284	0.013	21.453	0.000
CESD5		0.375	0.017	21.526	0.000
CESD6		0.456	0.021	21.403	0.000
I	ON				
SRH1		-0.522	0.013	-39.466	0.000
S	ON				
SRH1		0.140	0.028	4.971	0.000
I	WITH				
S		-0.199	0.037	-5.378	0.000
Means					
SRH1		0.000	0.014	0.000	1.000
Intercepts					
CESD1		0.000	0.000	999.000	999.000
CESD2		0.000	0.000	999.000	999.000
CESD3		0.000	0.000	999.000	999.000
CESD4		0.000	0.000	999.000	999.000
CESD5		0.000	0.000	999.000	999.000
CESD6		0.000	0.000	999.000	999.000
I		0.867	0.020	43.059	0.000
S		0.090	0.028	3.211	0.001
Variances					
SRH1		1.000	0.000	999.000	999.000
Residual Variances					
CESD1		0.475	0.011	41.759	0.000
CESD2		0.494	0.009	54.978	0.000
CESD3		0.496	0.008	61.429	0.000
CESD4		0.477	0.008	58.286	0.000
CESD5		0.457	0.009	52.931	0.000
CESD6		0.444	0.011	41.403	0.000
I		0.728	0.014	52.731	0.000
S		0.980	0.008	124.008	0.000

R-SQUARE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
CESD1	0.525	0.011	46.144	0.000
CESD2	0.506	0.009	56.376	0.000
CESD3	0.504	0.008	62.529	0.000
CESD4	0.523	0.008	64.033	0.000
CESD5	0.543	0.009	62.835	0.000
CESD6	0.556	0.011	51.942	0.000
Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
I	0.272	0.014	19.733	0.000
S	0.020	0.008	2.485	0.013

Plotting is the same as in the “Simple Slopes for Continuous Measured and Latent Variable Interactions” handout. Plots will be available by including the commands `PLOT: TYPE = plot2;` Go to the Plot menu and choose View Plots, then choose “Plot one parameter at a time”.



**lavaan code (excerpts)**

Because lavaan does not have programmable plots for models, I did not illustrate the plot of the simple slopes, but the lines could be easily plotted in R manually (please see the handout “Plotting Growth Curves: SPSS, R, and HLM” from my multilevel regression class for illustration, <http://web.pdx.edu/~newsomj/mlrclass>).

```
> library(QuantPsyc)
> d$srh1 = meanCenter(d$srh1)
> #always check to make sure centering worked
> #describe(d)
>
> library(lavaan)
> model = '
+ #specify growth loadings for intercept and slope factors
+ i =~ 1*cesd1 + 1*cesd2 + 1*cesd3 + 1*cesd4 + 1*cesd5 + 1*cesd6
+ s =~ 0*cesd1 + 1*cesd2 + 2*cesd3+ 3*cesd4 + 4*cesd5+ 5*cesd6
+
+ i ~ b2*srh1
+ s ~ b3*srh1
+
+ #estimate the covariance/correlation between intercept and slope
+ i =~ s
+ #estimate the intercept and slope factor means (value 1 means freely estimate the mean)
+ i ~ 1
+ s ~ b1*1
+
+ #set measurement intercepts to 0 because factor means are estimated
+ cesd1 ~ 0
+ cesd2 ~ 0
+ cesd3 ~ 0
+ cesd4 ~ 0
+ cesd5 ~ 0
+ cesd6 ~ 0
+
+ #freely estimate measurement residual variances (could set them equal for homogeneity of residuals)
+ cesd1 =~ cesd1
+ cesd2 =~ cesd2
+ cesd3 =~ cesd3
+ cesd4 =~ cesd4
+ cesd5 =~ cesd5
+ cesd6 =~ cesd6
+ srh1 =~ srh*srh1
+
+ #constraints for simple slopes
+
+ #NEW(LOW_W MED_W HIGH_W SIMP_LO SIMP_MED SIMP_HI);
+
+ #simple slope equations;
+ LOW_W := 3.521 - 1*(sqrt(srh)) ; #-1 SD below mean of W;
```

```

+ MED_W := 3.521 # mean of W;
+ HIGH_W := 3.521 + 1*(sqrt(srh)); # +1 SD below mean of W;
+
+ # Now calc simple slopes for each value of w;
+ SIMP_LO := b1 + b3*LOW_W;
+ SIMP_MED := b1 + b3*MED_W;
+ SIMP_HI := b1 + b3*HIGH_W;
+
>
> fit = sem(model,data = d,mimic = "Mplus",estimator="mlm")
> summary(fit,fit.measures=TRUE, rsquare=TRUE, standardized=TRUE)
lavaan 0.6-18 ended normally after 60 iterations
  
```

Estimator	ML					
Optimization method	NLMINB					
Number of model parameters	15					
Number of observations	5335					
Model Test User Model:						
Test Statistic	Standard	Scaled				
Degrees of freedom	286.284	286.781				
P-value (Chi-square)	20	20				
Scaling correction factor	0.000	0.000				
Satorra-Bentler correction (Mplus variant)		0.998				
Model Test Baseline Model:						
Test statistic	13320.570	13329.487				
Degrees of freedom	21	21				
P-value	0.000	0.000				
Scaling correction factor		0.999				
User Model versus Baseline Model:						
Comparative Fit Index (CFI)	0.980	0.980				
Tucker-Lewis Index (TLI)	0.979	0.979				
Robust Comparative Fit Index (CFI)		0.980				
Robust Tucker-Lewis Index (TLI)		0.979				
Loglikelihood and Information Criteria:						
Loglikelihood user model (H0)	-23588.057	-23588.057				
Loglikelihood unrestricted model (H1)	-23444.915	-23444.915				
Akaike (AIC)	47206.114	47206.114				
Bayesian (BIC)	47304.845	47304.845				
Sample-size adjusted Bayesian (SABIC)	47257.180	47257.180				
Root Mean Square Error of Approximation:						
RMSEA	0.050	0.050				
90 Percent confidence interval - lower	0.045	0.045				
90 Percent confidence interval - upper	0.055	0.055				
P-value H_0: RMSEA <= 0.050	0.494	0.488				
P-value H_0: RMSEA >= 0.080	0.000	0.000				
Robust RMSEA		0.050				
90 Percent confidence interval - lower		0.045				
90 Percent confidence interval - upper		0.055				
P-value H_0: Robust RMSEA <= 0.050		0.493				
P-value H_0: Robust RMSEA >= 0.080		0.000				
Standardized Root Mean Square Residual:						
SRMR	0.031	0.031				
Parameter Estimates:						
Standard errors	Robust.sem					
Information	Expected					
Information saturated (h1) model	Structured					
Latent Variables:						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
i =~						
cesd1	1.000				0.350	0.725
cesd2	1.000				0.350	0.728
cesd3	1.000				0.350	0.732
cesd4	1.000				0.350	0.737
cesd5	1.000				0.350	0.731
cesd6	1.000				0.350	0.710
s =~						
cesd1	0.000				0.000	0.000

cesd2	1.000				0.045	0.093
cesd3	2.000				0.090	0.188
cesd4	3.000				0.135	0.284
cesd5	4.000				0.180	0.375
cesd6	5.000				0.225	0.456
<b>Regressions:</b>						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
i ~						
srh1	(b2) -0.166	0.005	-34.478	0.000	-0.473	-0.522
s ~						
srh1	(b3) 0.006	0.001	5.080	0.000	0.127	0.140
<b>Covariances:</b>						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
.i ~~						
.s	-0.003	0.001	-4.358	0.000	-0.199	-0.199
<b>Intercepts:</b>						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
.i	0.304	0.005	58.021	0.000	0.867	0.867
.s	(b1) 0.004	0.001	3.249	0.001	0.090	0.090
.cesd1	0.000				0.000	0.000
.cesd2	0.000				0.000	0.000
.cesd3	0.000				0.000	0.000
.cesd4	0.000				0.000	0.000
.cesd5	0.000				0.000	0.000
.cesd6	0.000				0.000	0.000
srh1	0.000	0.015	0.000	1.000	0.000	0.000
<b>Variances:</b>						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
.cesd1	0.111	0.003	36.448	0.000	0.111	0.475
.cesd2	0.114	0.003	43.761	0.000	0.114	0.494
.cesd3	0.114	0.002	45.458	0.000	0.114	0.496
.cesd4	0.108	0.002	44.785	0.000	0.108	0.477
.cesd5	0.105	0.002	42.978	0.000	0.105	0.457
.cesd6	0.108	0.003	36.544	0.000	0.108	0.444
srh1	(srh) 1.217	0.024	51.679	0.000	1.217	1.000
.i	0.089	0.003	29.296	0.000	0.728	0.728
.s	0.002	0.000	10.569	0.000	0.980	0.980
<b>R-Square:</b>						
	Estimate					
cesd1	0.525					
cesd2	0.506					
cesd3	0.504					
cesd4	0.523					
cesd5	0.543					
cesd6	0.556					
i	0.272					
s	0.020					
<b>Defined Parameters:</b>						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
LOW_W	2.418	0.011	226.481	0.000	2.418	2.521
MED_W	3.521				3.521	3.521
HIGH_W	4.624	0.011	433.199	0.000	4.624	4.521
SIMP_LO	0.018	0.003	6.009	0.000	0.397	0.443
SIMP_MED	0.024	0.004	5.845	0.000	0.537	0.583
SIMP_HI	0.030	0.005	5.712	0.000	0.677	0.723

lavaan does not have the same type of plotting function as Mplus, so plots would need to be generated in R outside of lavaan. One option is to convert the data to long format and use the plotting approach I illustrate in my handout "Plotting Growth Curves: SPSS, R, and HLM" from my multilevel class page.