

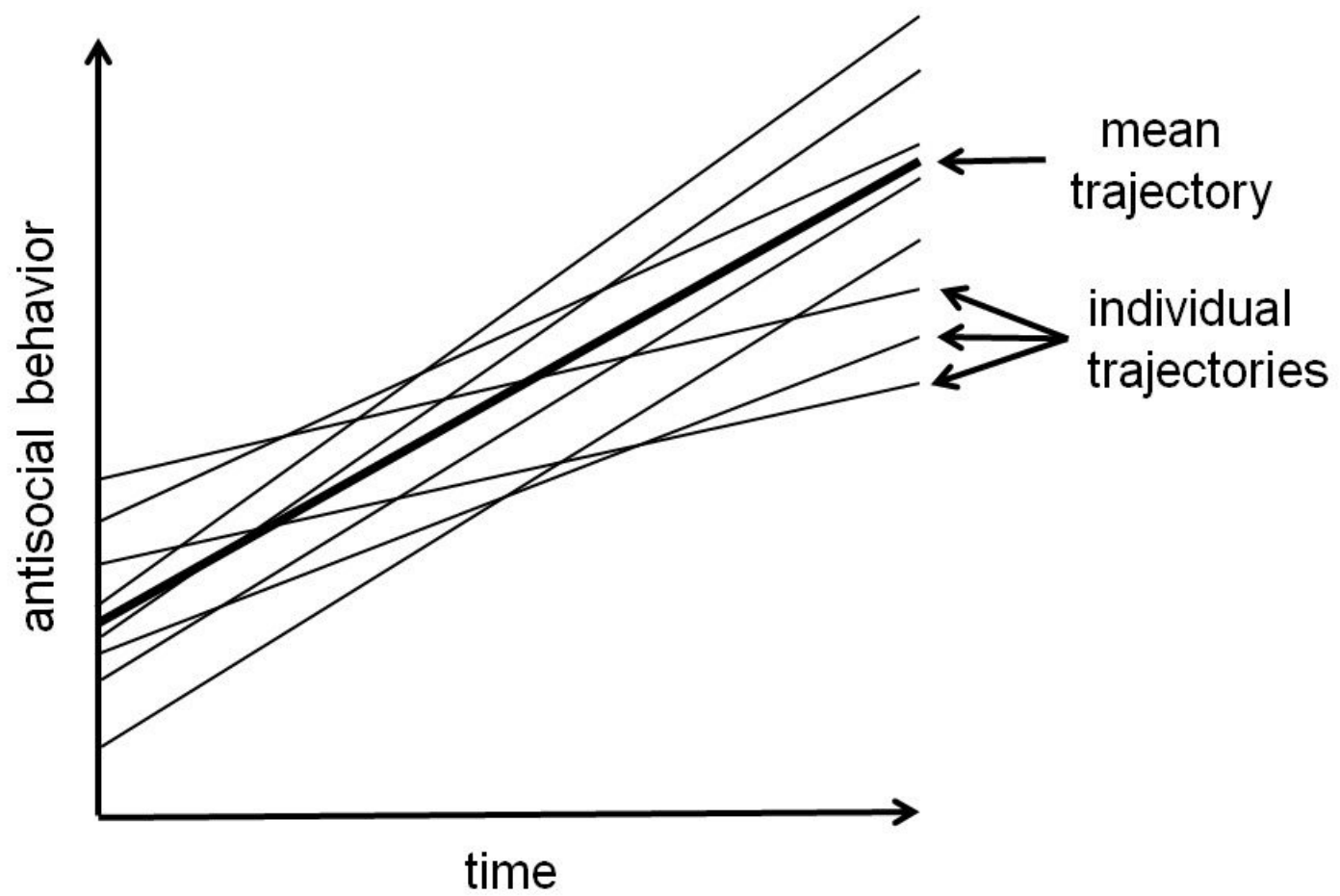
8. Structural Equation Modeling 5: Latent Growth Curve Models

References:

- Beaujean (2014). Chapter 5.
- Duncan, Duncan, & Strycker (2006). Chapter 2.

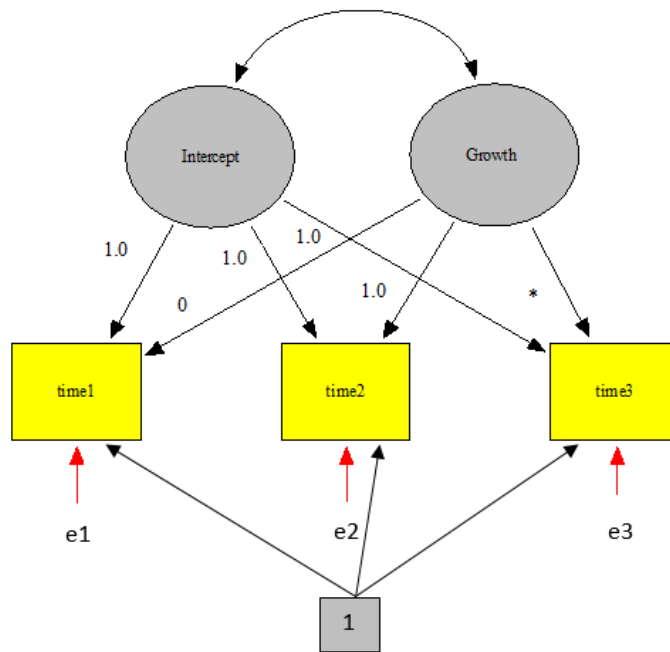
8.1. Introduction

- The latent growth curve modeling (LGM) is a special modeling technique based on mean and covariance structure analysis. Its purpose is to examine individual developmental trajectory (change) over time in a longitudinal study.
- Also known as latent growth modeling, growth curve modeling, or latent curve modeling (LCM).



8.2. The Two-factor LGM

- Theoretical model with 3 time points:



- The intercept factor (f_1) describes individuals' initial status at the onset of the study.
- The growth or slope factor (f_2) describes individuals' changes from one time point to another.

- Methodologically, LGM is a CFA model with a mean structure.
- Model equations:

$$\begin{aligned}\text{time1} &= V_1 = \mu_1 + 1.0*f_1 + 0*f_2 + e_1 \\ \text{time2} &= V_2 = \mu_2 + 1.0*f_1 + 1.0*f_2 + e_2 \\ \text{time3} &= V_3 = \mu_3 + 1.0*f_1 + \lambda_{32}*f_2 + e_3\end{aligned}$$

- In matrix form,

$$v = \mu + \Lambda f + e \quad (1)$$

- Taking expectations of the observed variables,

$$E(v) = \mu + \Lambda \alpha$$

where $\alpha = E(f)$ is the mean vector of the latent factors

- With 3 time points,

$$E(f_1) = \alpha_1$$

$$E(f_2) = \alpha_2$$

$$E(V_1) = \mu_1 + 1.0*\alpha_1 + 0*\alpha_2 = \mu_1 + \alpha_1$$

$$E(V_2) = \mu_2 + 1.0*\alpha_1 + 1.0*\alpha_2 = \mu_2 + \alpha_1 + \alpha_2$$

$$E(V_3) = \mu_3 + 1.0*\alpha_1 + \lambda_{32}*\alpha_2 = \mu_3 + \alpha_1 + \lambda_{32}\alpha_2$$

- In a two-factor LGM, the variables are:

Name	Type	Cause/Effect	dimension
v	observed	DV	$p \times 1$
f	latent	IV	$k \times 1$
e	latent	IV	$p \times 1$

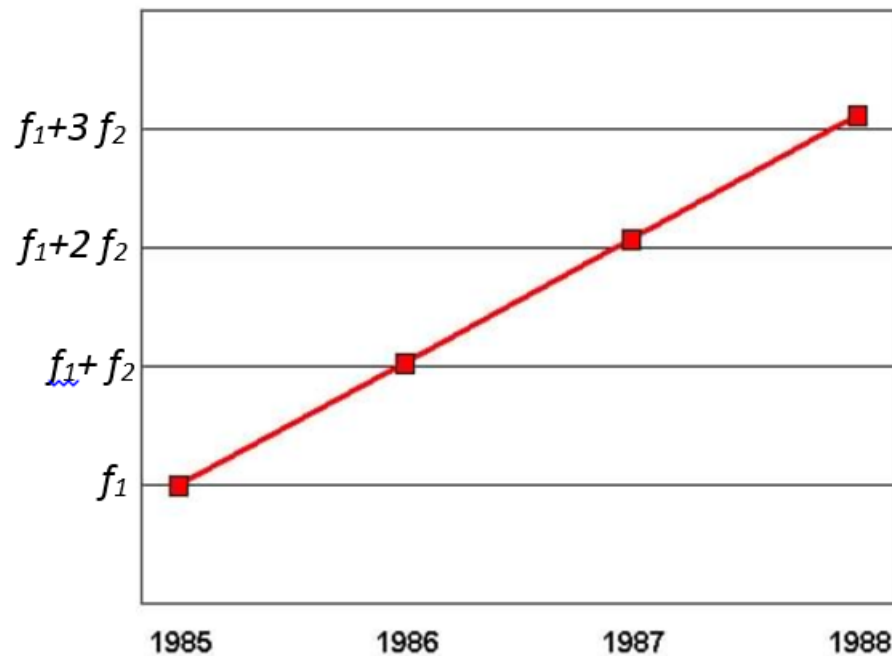
- And the parameter matrices are:

Parameter matrix	Symbol	Name	dimension
1) factor loading	Λ	lambda	$p \times k$
2) variance-covariance matrix of the factors	Ψ	psi	$k \times k$
3) variance-covariance matrix of errors	Θ	theta	$p \times p$
4) intercept of observed variables	μ	mu	$p \times 1$
5) latent means	α	alpha	$k \times 1$

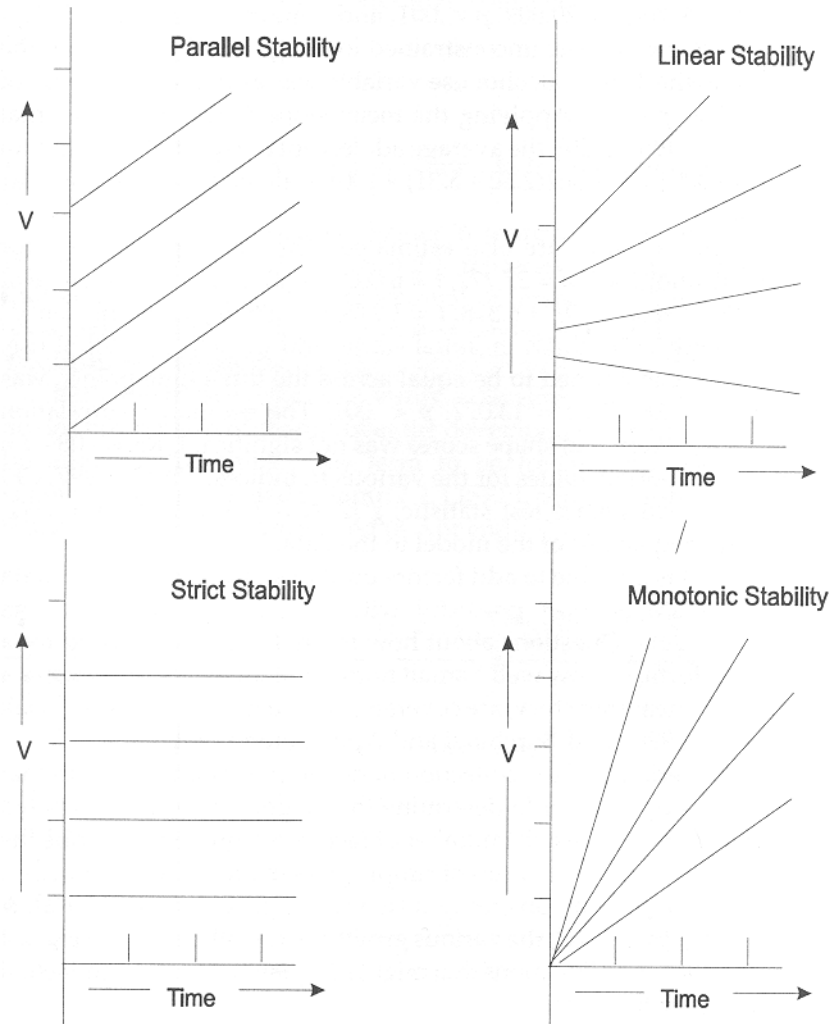
8.2.1. Interpreting the model parameters

- μ_1, μ_2, μ_3 are the intercepts, which will be the means of the observed variables if the latent means are zeros
- α_1 is the mean of f_1 , which measures the average initial status across individuals
- α_2 is the mean of f_2 , which measures the average growth across individuals
- λ_{32} is the factor loading, which characterizes the growth pattern over time, e.g., whether the pattern is linear or nonlinear
- ψ_{11} is the variance of f_1 , which measures how individuals are different in terms of their initial status
- ψ_{22} is the variance of f_2 , which measures how individuals are different in terms of their growth
- ψ_{21} is the covariance of f_1 and f_2 , which measures the relationship between initial status and growth

- $\theta_{11}, \theta_{22}, \theta_{33}$ are the error variances
- To fit a linear growth model, λ_{32} will become a fixed parameter with a known value.
- For example, $\lambda_{32} = 2$ and $\lambda_{42} = 3$ if four time points are selected with equal intervals.



- Different growth trajectories (Duncan et al., 2006; p.35)



8.3. Identification

- With 3 time points, the model cannot be identified because there are too many parameters for (1) mean structure and (2) covariance structure:

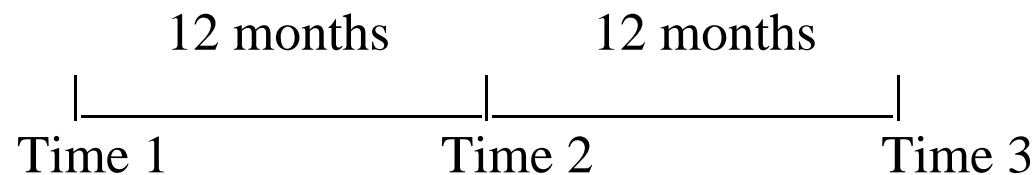
Structure	No. of information	No. of parameters	No. of constraints
Mean	3	$3 + 2 = 5$	3
Covariance	$(3 \times 4)/2 = 6$	$1 + 3 + 3 = 7$	2

- To overcome this, we typically (1) fix the intercepts of the observed variables at 0, that is, $\mu = (\mu_1, \mu_2, \mu_3)' = 0$, and (2) equate the error variances, that is, $\theta_{11} = \theta_{22} = \theta_{33}$
- For models with 4 or more time points, we may not need the equality of error variances constraints for identifying the covariance structure:

Structure	No. of information	No. of parameters	No. of constraints
Mean	4	$4 + 2 = 6$	4
Covariance	$(3 \times 4)/2 = 6$	$2 + 3 + 4 = 9$	0

8.4. Example 1: Alcohol Consumption

- In a longitudinal study of alcohol use, 343 participants were recruited. Each participant's level of alcohol consumption for the past 6 months was measured at three approximately equal time intervals over a 2-year period (Biglan et al., 1995):



- Data: ($N = 343$, filename = *biglan.dat*)

time1	1.000	0.486	0.399
time2	0.486	1.000	0.533
time3	0.399	0.533	1.000
SD	7.390	7.990	8.080
MEAN	8.310	10.000	10.810

- Questions

1. What is the average initial alcohol consumption?
2. Are people different in their initial consumption?
3. What is the average growth in alcohol consumption?
4. Are people different in their growth?
5. Is there any relationship between initial consumption and growth?
6. What is the growth pattern? Is it linear?

- Summary of findings:

Question	Parameter of Interest	Results
----------	-----------------------	---------

• Example 1 (continued):

filename: *biglan1.R* (R script)

```
# Example 1: Alcohol Consumption

# set work directory and load the packages
setwd("c:/users/wchan/google drive/stat6108/data")
library(lavaan)
library(semPlot)

# data preparation
alc.corr <- matrix(
c(1.000, 0.486, 0.399,
  0.486, 1.000, 0.533,
  0.399, 0.533, 1.000),
nrow=3, ncol=3)
alc.sd <- c(7.390, 7.990, 8.080)
alc.mean <- c(8.310, 10.000, 10.810)
varname <- c("time1", "time2", "time3")
alc.cov <- cor2cov(alc.corr, alc.sd, names=varname)
names(alc.mean) <- varname

# specify Model 1 (Evaluating linear growth using Wald test)
modell <- "
# measurement model
int =~ 1*time1 + 1*time2 + 1*time3
growth =~ 0*time1 + 1*time2 + 1a32*time3
# factor variance and covariance
int ~~ int + growth
growth ~~ growth
# error variance (constrained)
time1 ~~ c1*time1
time2 ~~ c1*time2
```

```

time3 ~~ c1*time3
# intercepts
time1 + time2 + time3 ~ 0*1
int + growth ~ 1
# evaluating linear growth
linear := 1a32-2"
# Fit Model 1 to data
fit1 <-lavaan(modell1, sample.cov=alc.cov, sample.mean=alc.mean, sample.nobs=343)

# specify Model 2 (Evaluating linear growth using LR test)
model2 <- "
# measurement model
int =~ 1*time1 + 1*time2 + 1*time3
growth =~ 0*time1 + 1*time2 + 2*time3
# error variance (constrained)
time1 ~~ c1*time1
time2 ~~ c1*time2
time3 ~~ c1*time3"
# Fit Model 2 to data
fit2 <-lavaan(model2, sample.cov=alc.cov, sample.mean=alc.mean, sample.nobs=343, auto.var=TRUE,
              auto.cov.lv.x=TRUE, meanstructure=TRUE, int.ov.free=FALSE, int.lv.free=TRUE)

# save the output
sink("biglan1.out", split=TRUE)
writeLines("\n Example 1: Alcohol Consumption\n")
writeLines("\n Output for Model 1 (Evaluating linear growth using Wald test)\n")
inspect(fit1)
summary(fit1, fit.measures=TRUE, standardized=TRUE)
writeLines("\n Output for Model 2 (Evaluating linear growth using LR test)\n")
summary(fit2, fit.measures=TRUE, standardized=TRUE)
writeLines("\n Model Comparisons\n")
lavTestLRT(fit1, fit2)
sink()

# create path diagram
semPaths(fit1,"path","est",nCharNodes=5)

```

filename: *biglan1.out* (output file)

Example 1: Alcohol Consumption

Output for Model 1 (Evaluating linear growth using Wald test)

Note: model contains equality constraints:

```

    lhs op rhs
1    5 ==    6
2    5 ==    7

$lambda
      int growth
time1    0      0
time2    0      0
time3    0      1

$theta
      time1 time2 time3
time1  5
time2  0      6
time3  0      0      7

$psi
      int growth
int      2
growth 3    4

$nu
      intrcp
time1    0
time2    0
time3    0

```


\$alpha

```
      intrcp
int      8
growth   9
```

lavaan 0.6-3 ended normally after 67 iterations

Optimization method	NLMINB
Number of free parameters	9
Number of equality constraints	2
Number of observations	343
Estimator	ML
Model Fit Test Statistic	2.468
Degrees of freedom	2
P-value (Chi-square)	0.291

Model test baseline model:

Minimum Function Test Statistic	219.563
Degrees of freedom	3
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.998
Tucker-Lewis Index (TLI)	0.997

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-3465.563
Loglikelihood unrestricted model (H1)	-3464.329
Number of free parameters	7
Akaike (AIC)	6945.125

Bayesian (BIC)	6971.990
Sample-size adjusted Bayesian (BIC)	6949.784

Root Mean Square Error of Approximation:

RMSEA	0.026
90 Percent Confidence Interval	0.000 0.114
P-value RMSEA <= 0.05	0.550

Standardized Root Mean Square Residual:

SRMR	0.029
------	-------

Parameter Estimates:

Information	Expected
Information saturated (h1) model	Structured
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int =~						
time1	1.000				5.262	0.702
time2	1.000				5.262	0.678
time3	1.000				5.262	0.644
growth =~						
time1	0.000				0.000	0.000
time2	1.000				2.505	0.323
time3 (1a32)	1.496	0.258	5.794	0.000	3.748	0.459

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int ~~						
growth	-1.156	2.971	-0.389	0.697	-0.088	-0.088

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1	0.000				0.000	0.000
.time2	0.000				0.000	0.000
.time3	0.000				0.000	0.000
int	8.314	0.402	20.669	0.000	1.580	1.580
growth	1.674	0.389	4.307	0.000	0.668	0.668

Variances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int		27.687	4.608	6.008	0.000	1.000	1.000
growth		6.276	3.535	1.775	0.076	1.000	1.000
.time1	(psi)	28.530	2.179	13.096	0.000	28.530	0.507
.time2	(psi)	28.530	2.179	13.096	0.000	28.530	0.474
.time3	(psi)	28.530	2.179	13.096	0.000	28.530	0.427

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
linear	-0.504	0.258	-1.950	0.051	1.748	-1.541

Output for Model 2 (Evaluating linear growth using LR test)

lavaan 0.6-3 ended normally after 55 iterations

Optimization method	NLMINB
Number of free parameters	8
Number of equality constraints	2
Number of observations	343
Estimator	ML
Model Fit Test Statistic	4.614
Degrees of freedom	3
P-value (Chi-square)	0.202

Model test baseline model:

Minimum Function Test Statistic	219.563
Degrees of freedom	3
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.993
Tucker-Lewis Index (TLI)	0.993

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-3466.636
Loglikelihood unrestricted model (H1)	-3464.329
Number of free parameters	6
Akaike (AIC)	6945.271
Bayesian (BIC)	6968.298
Sample-size adjusted Bayesian (BIC)	6949.264

Root Mean Square Error of Approximation:

RMSEA		0.040
90 Percent Confidence Interval	0.000	0.107
P-value RMSEA <= 0.05		0.508

Standardized Root Mean Square Residual:

SRMR	0.041
------	-------

Parameter Estimates:

Information	Expected
Information saturated (h1) model	Structured
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int =~						
time1	1.000				5.335	0.707
time2	1.000				5.335	0.697
time3	1.000				5.335	0.648
growth =~						
time1	0.000				0.000	0.000
time2	1.000				1.944	0.254
time3	2.000				3.888	0.472

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int ~~						
growth	-1.056	2.145	-0.492	0.622	-0.102	-0.102

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1	0.000				0.000	0.000
.time2	0.000				0.000	0.000

.time3	0.000				0.000	0.000
int	8.457	0.390	21.682	0.000	1.585	1.585
growth	1.250	0.229	5.455	0.000	0.643	0.643

Variances:

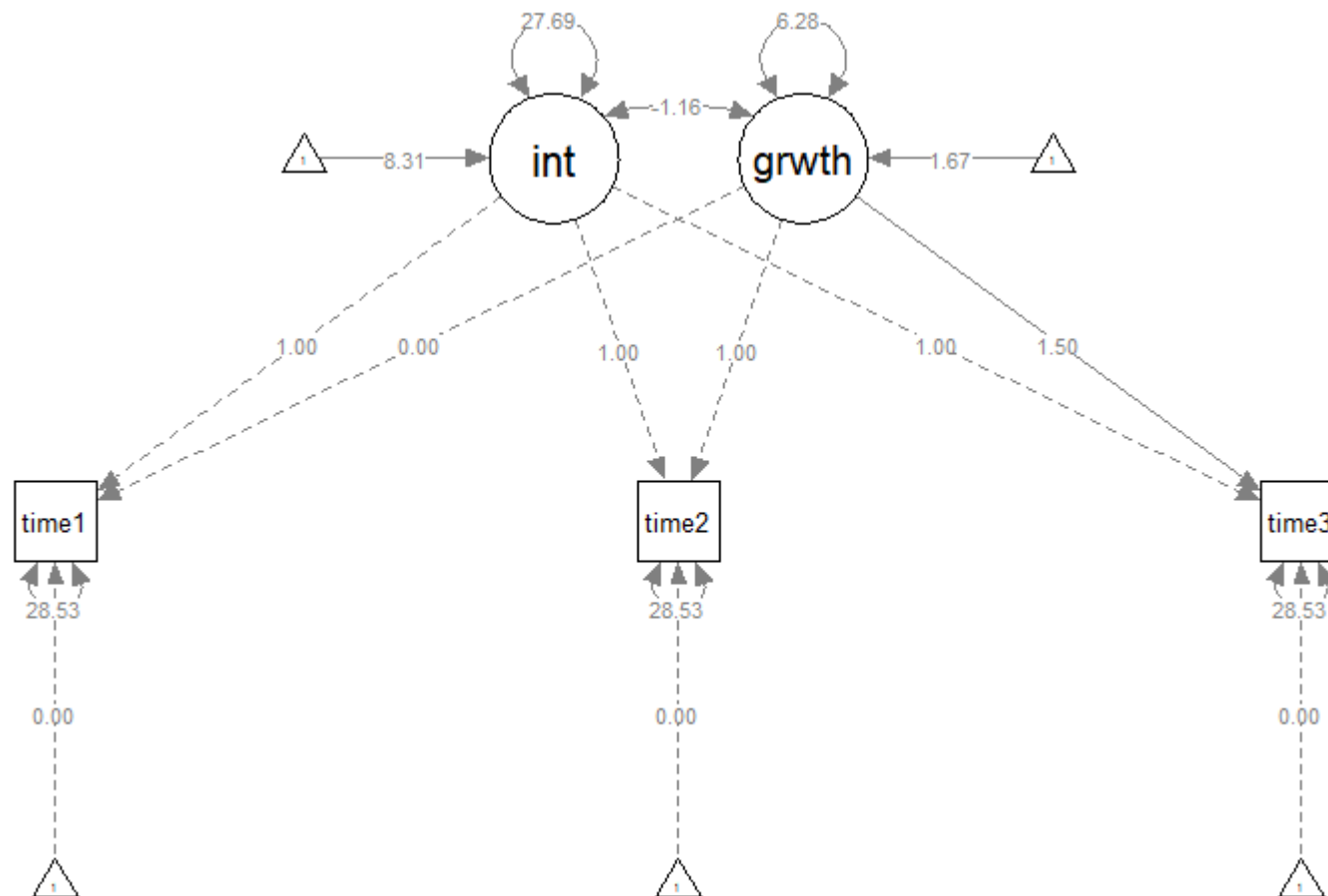
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1	(psi)	28.460	2.173	13.096	0.000	28.460	0.500
.time2	(psi)	28.460	2.173	13.096	0.000	28.460	0.486
.time3	(psi)	28.460	2.173	13.096	0.000	28.460	0.420
int		28.464	4.377	6.503	0.000	1.000	1.000
growth		3.780	1.753	2.156	0.031	1.000	1.000

Model Comparisons

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
fit1	2	6945.1	6972.0	2.4680			
fit2	3	6945.3	6968.3	4.6137	2.1456	1	0.143

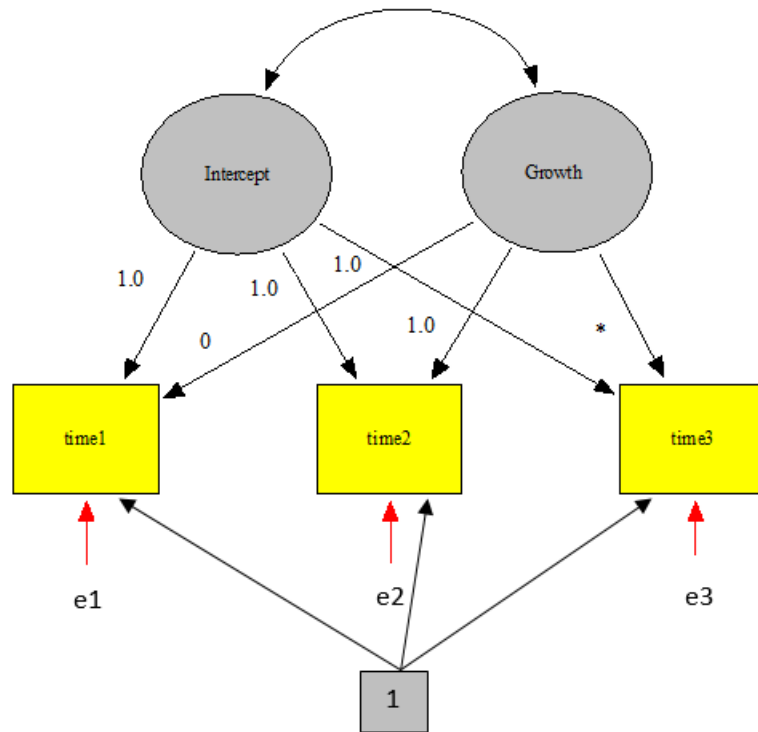
```
> library(semPlot)
> semPaths(fit1,"path","est",nCharNodes=5)
```



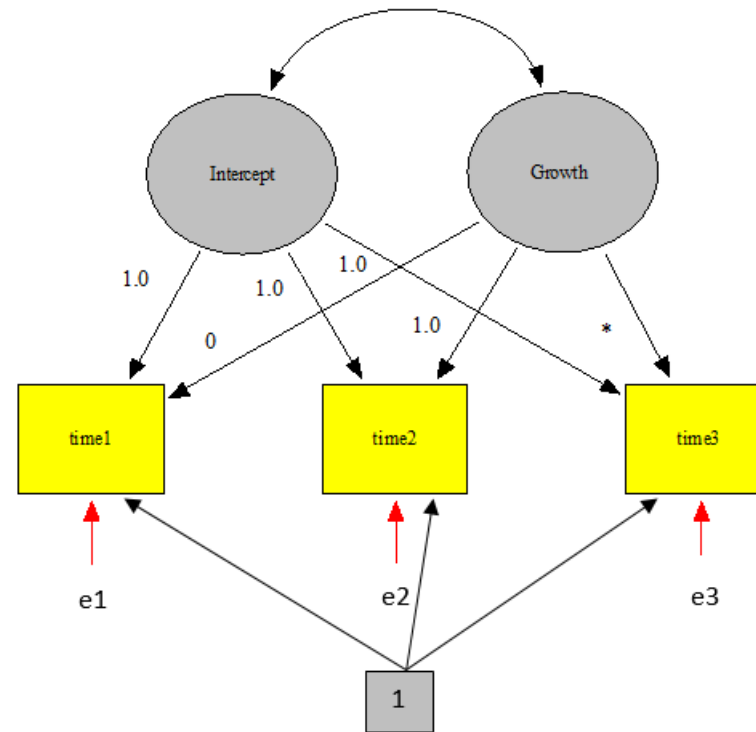
8.5. Multisample LGM

- To determine whether a common developmental model exists, or whether there are different growth patterns across groups (Duncan et al., 2006; Ch. 5)

Group 1:



Group 2:



8.5.1. Identification

- For the covariance structure, since the factor loading matrix has a specific pattern with some fixed values, we can estimate the variances of the latent factors
- For the mean structure, we are interested in estimating α , the latent means of the intercept and growth factors. This is achieved by setting the intercept $\mu = 0$ in each group

8.6. Example 2: Comparing Alcohol Use Between Females and Males

- In a longitudinal study of adolescent alcohol use, 196 females and 95 males were recruited. Each participant's level of alcohol consumption for the past 6 months was measured at three approximately equal time intervals over a 2-year period (Biglan et al., 1995).

- Data:

Female ($N_1 = 196$)

(filename = *female.dat*)

time1	1.0000	0.4641	0.4200
time2	0.4641	1.0000	0.5614
time3	0.4200	0.5614	1.0000
SD	1.3282	1.5136	1.5346
MEAN	1.4430	1.7230	1.8310

Male ($N_2 = 95$)

(filename = *male.dat*)

1.0000	0.4708	0.3915
0.4708	1.0000	0.6679
0.3915	0.6679	1.0000
1.3932	1.4910	1.6520
1.5540	1.8640	2.2800

- Questions:

1. Do they have equal growth pattern?
2. Are females (males) different in their initial alcohol use and growth?
3. Are such differences identical between female and male drinkers?
4. Do the two groups have equal average initial status?
5. Do they have equal average growth?

- Summary of findings:

Question	Parameter of Interest		Results
	Females	Males	

• Example 2 (continued):

filename: *biglan2.R* (R script)

```
# Example 2: Comparing Alcohol Use Between Females and Males
```

```
# set work directory and load lavaan packages
setwd("c:/users/wchan/google drive/stat6108/data")
library(lavaan)
```

```
# data preparation
```

```
# group 1: Females
```

```
female.corr <- matrix(
c(1.0000, 0.4641, 0.4200,
  0.4641, 1.0000, 0.5614,
  0.4200, 0.5614, 1.0000),
nrow=3, ncol=3)
female.sd <- c(1.3282, 1.5136, 1.5346)
female.mean <- c(1.4430, 1.7230, 1.8310)
```

```
# group 2: Males
```

```
male.corr <- matrix(
c(1.0000, 0.4708, 0.3915,
  0.4708, 1.0000, 0.6679,
  0.3915, 0.6679, 1.0000),
nrow=3, ncol=3)
male.sd <- c(1.3932, 1.4910, 1.6520)
male.mean <- c(1.5540, 1.8640, 2.2800)
```

```
varname <- c("time1", "time2", "time3")
female.cov <- cor2cov(female.corr, female.sd, names=varname)
male.cov <- cor2cov(male.corr, male.sd, names=varname)
names(female.mean) <- names(male.mean) <- varname
```

```

# specify Model 1 (Using Wald test to compare the groups)
modell1 <- "
# measurement model
int =~ 1*time1 + 1*time2 + 1*time3
growth =~ 0*time1 + 1*time2 + c(la1,la2)*time3
# factor variance and covariance
int ~~ c(ps11,ps12)*int
growth ~~ c(ps21,ps22)*growth
int ~~ c(ps31,ps32)*growth
# error variance (constrained)
time1 ~~ c(theta1,theta2)*time1
time2 ~~ c(theta1,theta2)*time2
time3 ~~ c(theta1,theta2)*time3
# intercepts and factor means
time1 + time2 + time3 ~ 0*1
int ~ c(al11,al12)*1
growth ~ c(al21,al22)*1
# comparing females and males
la_d := la1-la2
ps1_d := ps11-ps12
ps2_d := ps21-ps22
ps3_d := ps31-ps32
al1_d := al11-al12
al2_d := al21-al22
"
# Fit Model 1 to data
fit1 <-lavaan(modell1, sample.cov=list(Females=female.cov, Males=male.cov),
sample.mean=list(Females=female.mean, Males=male.mean),
               sample.nobs=c(196, 95))

```

```

# specify Model 2 (Using LRT test to compare the groups)
model2 <- "
# measurement model
int =~ 1*time1 + 1*time2 + 1*time3
growth =~ 0*time1 + 1*time2 + time3
# error variance (constrained)
time1 ~~ c(theta1,theta2)*time1
time2 ~~ c(theta1,theta2)*time2
time3 ~~ c(theta1,theta2)*time3
"

# Fit Model 2 to data
fit2 <-lavaan(model2, sample.cov=list(Females=female.cov, Males=male.cov),
sample.mean=list(Females=female.mean, Males=male.mean),
               sample.nobs=c(196, 95), auto.var=TRUE, auto.cov.lv.x=TRUE, meanstructure=TRUE,
int.ov.free=FALSE, int.lv.free=TRUE,
               group.equal=c("loadings","lv.variances","lv.covariances","means"))

# save the output
sink("biglan2.out", split=TRUE)
writeLines("\n Example 2: Comparing Alcohol Use Between Females and Males\n")
writeLines("\n Output for Model 1 (Using Wald test to compare the groups)\n")
summary(fit1, fit.measures=TRUE, standardized=TRUE)
writeLines("\n Output for Model 2 (Using LRT test to compare the groups)\n")
summary(fit2, fit.measures=TRUE, standardized=TRUE)
lavTestLRT(fit1,fit2)
sink()

```

filename: *biglan2.out* (output file)

Example 2: Comparing Alcohol Use Between Females and Males

Output for Model 1 (Using Wald test to compare the groups)

lavaan 0.6-3 ended normally after 50 iterations

Optimization method	NLMINB
Number of free parameters	18
Number of equality constraints	4

Number of observations per group	
Females	196
Males	95

Estimator	ML
Model Fit Test Statistic	2.553
Degrees of freedom	4
P-value (Chi-square)	0.635

Chi-square for each group:

Females	0.712
Males	1.841

Model test baseline model:

Minimum Function Test Statistic	212.491
Degrees of freedom	6
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	1.000
-----------------------------	-------

Tucker-Lewis Index (TLI) 1.011

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-1468.702
Loglikelihood unrestricted model (H1)	-1467.425
Number of free parameters	14
Akaike (AIC)	2965.404
Bayesian (BIC)	3016.830
Sample-size adjusted Bayesian (BIC)	2972.433

Root Mean Square Error of Approximation:

RMSEA	0.000
90 Percent Confidence Interval	0.000 0.102
P-value RMSEA ≤ 0.05	0.770

Standardized Root Mean Square Residual:

SRMR	0.023
------	-------

Parameter Estimates:

Information	Expected
Information saturated (h1) model	Structured
Standard Errors	Standard

Group 1 [Females]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int =~						
time1	1.000				0.885	0.663
time2	1.000				0.885	0.596

time3		1.000				0.885	0.572
growth =~							
time1		0.000				0.000	0.000
time2		1.000				0.482	0.324
time3	(la1)	1.270	0.286	4.437	0.000	0.611	0.395

Covariances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int =~							
growth	(ps31)	0.095	0.149	0.640	0.522	0.224	0.224

Intercepts:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1		0.000				0.000	0.000
.time2		0.000				0.000	0.000
.time3		0.000				0.000	0.000
int	(al11)	1.440	0.095	15.163	0.000	1.627	1.627
growth	(al21)	0.299	0.096	3.103	0.002	0.620	0.620

Variances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int	(ps11)	0.783	0.202	3.870	0.000	1.000	1.000
growth	(ps21)	0.232	0.192	1.207	0.227	1.000	1.000
.time1	(tht1)	0.996	0.101	9.899	0.000	0.996	0.560
.time2	(tht1)	0.996	0.101	9.899	0.000	0.996	0.452
.time3	(tht1)	0.996	0.101	9.899	0.000	0.996	0.416

Group 2 [Males]:

Latent Variables:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int =~							
time1		1.000				1.057	0.766
time2		1.000				1.057	0.727
time3		1.000				1.057	0.631

growth =~							
time1		0.000				0.000	0.000
time2		1.000				0.663	0.456
time3	(la2)	1.717	0.308	5.567	0.000	1.139	0.680

Covariances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int	~~						
growth	(ps32)	-0.115	0.170	-0.680	0.497	-0.165	-0.165

Intercepts:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1		0.000				0.000	0.000
.time2		0.000				0.000	0.000
.time3		0.000				0.000	0.000
int	(al12)	1.523	0.140	10.897	0.000	1.440	1.440
growth	(al22)	0.416	0.123	3.382	0.001	0.626	0.626

Variances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int	(ps12)	1.118	0.282	3.960	0.000	1.000	1.000
growth	(ps22)	0.440	0.218	2.016	0.044	1.000	1.000
.time1	(tht2)	0.788	0.114	6.892	0.000	0.788	0.413
.time2	(tht2)	0.788	0.114	6.892	0.000	0.788	0.373
.time3	(tht2)	0.788	0.114	6.892	0.000	0.788	0.281

Defined Parameters:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
la_d		-0.447	0.421	-1.063	0.288	-0.528	-0.285
ps1_d		-0.335	0.347	-0.964	0.335	0.000	0.000
ps2_d		-0.208	0.291	-0.716	0.474	0.000	0.000
ps3_d		0.211	0.226	0.933	0.351	0.388	0.388
al1_d		-0.083	0.169	-0.492	0.623	0.187	0.187
al2_d		-0.117	0.156	-0.750	0.453	-0.006	-0.006

Output for Model 2 (Using LRT test to compare the groups)

lavaan 0.6-3 ended normally after 32 iterations

Optimization method	NLMINB
Number of free parameters	18
Number of equality constraints	10
Number of observations per group	
Females	196
Males	95
Estimator	ML
Model Fit Test Statistic	10.518
Degrees of freedom	10
P-value (Chi-square)	0.396

Chi-square for each group:

Females	3.811
Males	6.707

Model test baseline model:

Minimum Function Test Statistic	212.491
Degrees of freedom	6
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.997
Tucker-Lewis Index (TLI)	0.998

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-1472.684
-------------------------------	-----------

Loglikelihood unrestricted model (H1)	-1467.425
Number of free parameters	8
Akaike (AIC)	2961.368
Bayesian (BIC)	2990.755
Sample-size adjusted Bayesian (BIC)	2965.385

Root Mean Square Error of Approximation:

RMSEA		0.019
90 Percent Confidence Interval	0.000	0.093
P-value RMSEA ≤ 0.05		0.667

Standardized Root Mean Square Residual:

SRMR	0.065
------	-------

Parameter Estimates:

Information	Expected
Information saturated (h1) model	Structured
Standard Errors	Standard

Group 1 [Females]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int =~						
time1	1.000				0.959	0.704
time2	1.000				0.959	0.651
time3	1.000				0.959	0.596
growth =~						
time1	0.000				0.000	0.000
time2	1.000				0.563	0.382
time3 (.p6.)	1.522	0.226	6.734	0.000	0.857	0.532

Covariances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int ~~							
growth	(.12.)	-0.000	0.105	-0.002	0.998	-0.000	-0.000

Intercepts:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1		0.000				0.000	0.000
.time2		0.000				0.000	0.000
.time3		0.000				0.000	0.000
int	(.16.)	1.470	0.079	18.668	0.000	1.533	1.533
growth	(.17.)	0.324	0.074	4.374	0.000	0.575	0.575

Variances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1	(tht1)	0.937	0.088	10.623	0.000	0.937	0.505
.time2	(tht1)	0.937	0.088	10.623	0.000	0.937	0.431
.time3	(tht1)	0.937	0.088	10.623	0.000	0.937	0.362
int	(.10.)	0.920	0.163	5.642	0.000	1.000	1.000
growth	(.11.)	0.317	0.137	2.307	0.021	1.000	1.000

Group 2 [Males]:

Latent Variables:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int =~							
time1		1.000				0.959	0.712
time2		1.000				0.959	0.657
time3		1.000				0.959	0.601
growth =~							
time1		0.000				0.000	0.000
time2		1.000				0.563	0.386
time3	(.p6.)	1.522	0.226	6.734	0.000	0.857	0.537

Covariances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
int ~~							
growth	(.12.)	-0.000	0.105	-0.002	0.998	-0.000	-0.000

Intercepts:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1		0.000				0.000	0.000
.time2		0.000				0.000	0.000
.time3		0.000				0.000	0.000
int	(.16.)	1.470	0.079	18.668	0.000	1.533	1.533
growth	(.17.)	0.324	0.074	4.374	0.000	0.575	0.575

Variances:

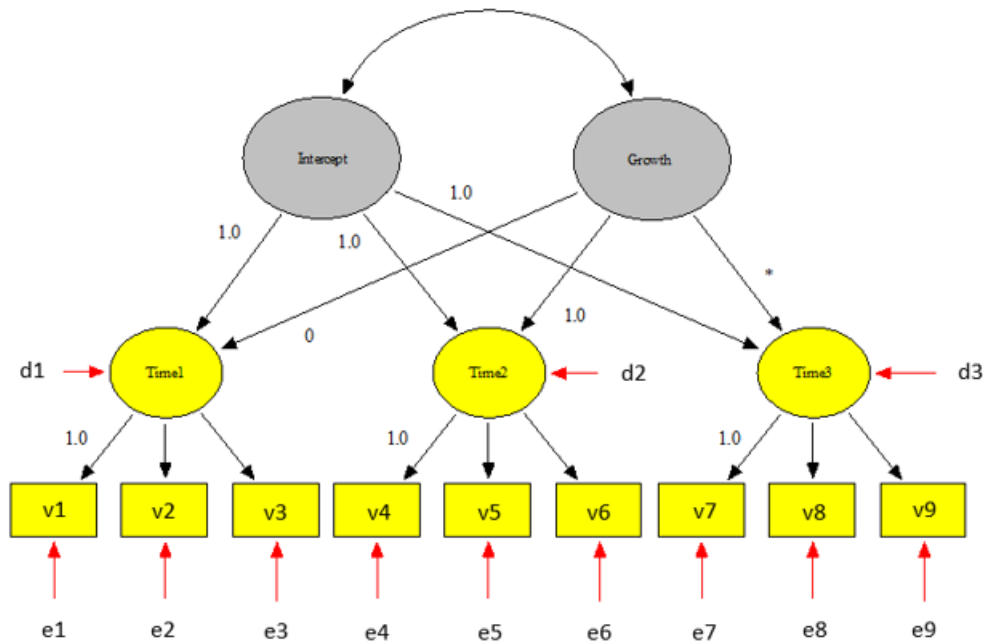
		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.time1	(tht2)	0.894	0.113	7.942	0.000	0.894	0.493
.time2	(tht2)	0.894	0.113	7.942	0.000	0.894	0.420
.time3	(tht2)	0.894	0.113	7.942	0.000	0.894	0.351
int	(.10.)	0.920	0.163	5.642	0.000	1.000	1.000
growth	(.11.)	0.317	0.137	2.307	0.021	1.000	1.000

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
fit1	4	2965.4	3016.8	2.5531			
fit2	10	2961.4	2990.8	10.5177	7.9646	6	0.2407

8.7. LGM with Multiple Indicators

- To determine a growth model of a set of related measures (e.g., language ability, logical reasoning, memory) simultaneously (Duncan et al., 2006; Ch. 4)
- Curve-of-factors LGM (McArdle, 1988)



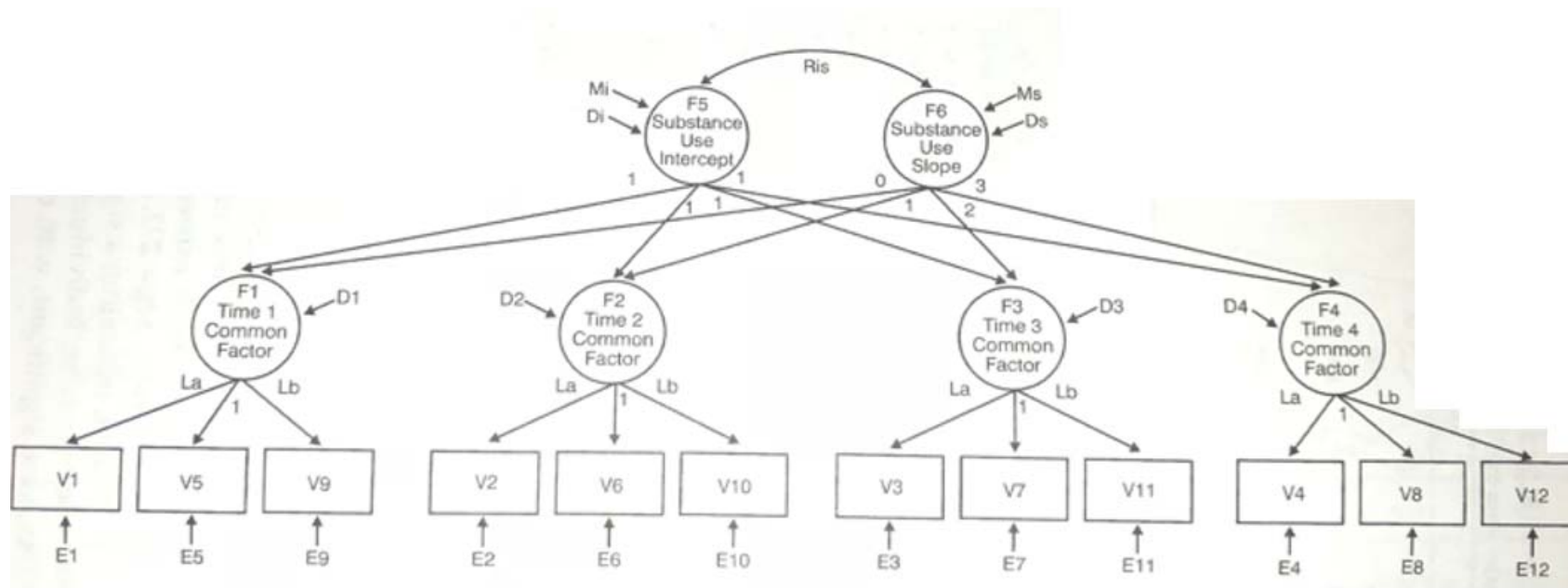
V1, V2, V3 = Time 1 indicators (e.g., language, logic, memory test score) measuring Time 1 Factor (e.g., intelligence)
V4, V5, V6 = Time 2 indicators (e.g., language, logic, memory test score) measuring Time 2 Factor (e.g., intelligence)
V7, V8, V9 = Time 3 indicators (e.g., language, logic, memory test score) measuring Time 3 Factor (e.g., intelligence)

- For metric invariance, factor loadings of the same variable are constrained to be equal across time (i.e., $\lambda_{21}=\lambda_{52}=\lambda_{83}$; $\lambda_{31}=\lambda_{62}=\lambda_{93}$)
- In order to estimate the mean of the intercept and growth factor, α_1 and α_2 , we need to fix (1) the intercept of the time factors at zeros (i.e., $\alpha_3=\alpha_4=\alpha_5=0$), and (2) the intercepts of the reference variables (V1, V4, V7) at zeros (i.e., $\mu_1=\mu_4=\mu_7=0$)
- Errors of the same variable are allowed to covary to improve model fit

$$\Psi_e = \begin{bmatrix} \psi_{11} & & & & & & & & \\ & \psi_{22} & & & & & & & \\ & & \psi_{33} & & & & & & \\ \psi_{41} & & & \psi_{44} & & & & & \\ & \psi_{52} & & & \psi_{55} & & & & \\ & & \psi_{63} & & & \psi_{66} & & & \\ \psi_{71} & & & \psi_{74} & & & \psi_{77} & & \\ & \psi_{82} & & & \psi_{85} & & & \psi_{88} & \\ & & \psi_{93} & & & \psi_{96} & & & \psi_{99} \end{bmatrix}$$

8.8. Example 3: Drug Use

- In a longitudinal study of drug use, 3 indicators were used to measure the factor: alcohol use, tobacco use, and marijuana use. 357 participants were recruited and each participant's level of substances consumption for the past 6 months was measured at four approximately equal time intervals (Duncan et al., 2006, Ch. 4)



- Data ($N = 357$, filename=*drug.dat*)

Table 4.1

Descriptive Statistics for Adolescent Alcohol, Tobacco, and Marijuana Use

	<i>Alcohol Use</i>				<i>Tobacco Use</i>				<i>Marijuana Use</i>			
	<i>T1</i>	<i>T2</i>	<i>T3</i>	<i>T4</i>	<i>T1</i>	<i>T2</i>	<i>T3</i>	<i>T4</i>	<i>T1</i>	<i>T2</i>	<i>T3</i>	<i>T4</i>
	<i>V1</i>	<i>V2</i>	<i>V3</i>	<i>V4</i>	<i>V5</i>	<i>V6</i>	<i>V7</i>	<i>V8</i>	<i>V9</i>	<i>V10</i>	<i>V11</i>	<i>V12</i>
V1	1.000											
V2	.725	1.000										
V3	.595	.705	1.000									
V4	.566	.624	.706	1.000								
V5	.419	.281	.303	.283	1.000							
V6	.344	.362	.350	.367	.671	1.000						
V7	.224	.281	.353	.360	.548	.783	1.000					
V8	.183	.234	.300	.384	.458	.696	.823	1.000				
V9	.579	.482	.410	.303	.455	.333	.244	.179	1.000			
V10	.532	.571	.501	.440	.347	.444	.352	.272	.663	1.000		
V11	.439	.507	.648	.496	.378	.419	.430	.345	.551	.709	1.000	
V12	.431	.469	.527	.571	.345	.424	.427	.412	.499	.682	.736	1.000
M	1.338	1.591	2.019	2.364	.862	1.218	1.445	1.756	.554	.890	1.033	1.123
SD	1.260	1.334	1.440	1.376	1.709	1.948	2.117	2.265	1.199	1.432	1.496	1.503

Note. Correlation matrix is in the triangle; means and standard deviations are presented in the bottom rows of the matrix.

- Summary of findings:
 1. Average initial status
 2. Average growth
 3. Variability of people's initial status
 4. Variability of people's growth
 5. Relationship between initial status and growth
 6. Pattern of growth

filename: *drug.R* (R script file)

Example 3: Drug Use

```
# set work directory and load lavaan package
setwd("c:/users/wchan/google drive/stat6108/data")
library(lavaan)
```

```
# data preparation
data <- read.table("drug.dat")
data <- as.matrix(data)
corr <- data[1:12,]
sd <- data[13,]
mean <- data[14,]
cov <- cor2cov(corr, sd)
rownames(cov) <- colnames(cov)
```

```
# specify Model 1 (Curve-of-factors LGM)
modell <- "
# measurement model
Time1 =~ la1*V1 + 1*V5 + la2*V9
Time2 =~ la1*V2 + 1*V6 + la2*V10
Time3 =~ la1*V3 + 1*V7 + la2*V11
Time4 =~ la1*V4 + 1*V8 + la2*V12
Int =~ 1*Time1 + 1*Time2 + 1*Time3 + 1*Time4
Growth =~ 0*Time1 + 1*Time2 + la3*Time3 + la4*Time4
```

```
# error variance
V1 ~~ V1 + V2 + V3 + V4
V2 ~~ V2 + V3 + V4
V3 ~~ V3 + V4
V4 ~~ V4
V5 ~~ V5 + V6 + V7 + V8
V6 ~~ V6 + V7 + V8
```

```

V7 ~~ V7 + V8
V8 ~~ V8
V9 ~~ V9 + V10 + V11 + V12
V10 ~~ V10 + V11 + V12
V11 ~~ V11 + V12
V12 ~~ V12

# intercepts
Time1 + Time2 + Time3 + Time4 ~ 0*1
Int + Growth ~ 1
V1 + V2 + V3 + V4 ~ 0*1
V5 + V6 + V7 + V8 + V9 + V10 + V11 + V12 ~ 1

# evaluating linear growth
linear1 := la3-2
linear2 := la4-3
"

# Fit Model 1 to data
fit1 <- lavaan(model1, sample.cov=cov, sample.mean=mean, sample.nobs=357, auto.var=TRUE,
auto.cov.lv.x=TRUE)

# specify Model 2 (Testing Linear Growth using LR test)
model2 <- "
# measurement model
Time1 =~ la*V1 + 1*V5 + 1b*V9
Time2 =~ la*V2 + 1*V6 + 1b*V10
Time3 =~ la*V3 + 1*V7 + 1b*V11
Time4 =~ la*V4 + 1*V8 + 1b*V12
Int =~ 1*Time1 +1*Time2 + 1*Time3 + 1*Time4
Growth =~ 0*Time1 +1*Time2 + 2*Time3 + 3*Time4

# error variance
V1 ~~ V1 + V2 + V3 + V4
V2 ~~ V2 + V3 + V4
V3 ~~ V3 + V4

```

```

V4 ~~ V4
V5 ~~ V5 + V6 + V7 + V8
V6 ~~ V6 + V7 + V8
V7 ~~ V7 + V8
V8 ~~ V8
V9 ~~ V9 + V10 + V11 + V12
V10 ~~ V10 + V11 + V12
V11 ~~ V11 + V12
V12 ~~ V12

# intercepts
Time1 + Time2 + Time3 + Time4 ~ 0*1
Int + Growth ~ 1
V1 + V2 + V3 + V4 ~ 0*1
V5 + V6 + V7 + V8 + V9 + V10 + V11 + V12 ~ 1
"

# Fit Model 2 to data
fit2 <-lavaan(model2, sample.cov=cov, sample.mean=mean, sample.nobs=357, auto.var=TRUE,
auto.cov.lv.x=TRUE)

# save the output
sink("drug.out", split=TRUE)
writeLines("\n Example 3: Drug Use\n")
writeLines("\n Output for Model 1 (Curve-of-factors LGM)\n")
summary(fit1, fit.measures=TRUE, standardized=TRUE)
writeLines("\n Output for Model 2 (Testing Linear Growth using LRT)\n")
summary(fit2, fit.measures=TRUE, standardized=TRUE)
writeLines("\n Model Comparisons\n")
lavTestLRT(fit1, fit2)
sink()

```

filename: *drug.out* (output file)

Example 3: Drug Use

Output for Model 1 (Curve-of-factors LGM)

lavaan 0.6-3 ended normally after 87 iterations

Optimization method	NLMINB
Number of free parameters	57
Number of equality constraints	6

Number of observations	357
------------------------	-----

Estimator	ML
Model Fit Test Statistic	76.481
Degrees of freedom	39
P-value (Chi-square)	0.000

Model test baseline model:

Minimum Function Test Statistic	3173.220
Degrees of freedom	66
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.988
Tucker-Lewis Index (TLI)	0.980

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-6425.102
Loglikelihood unrestricted model (H1)	-6386.861

Number of free parameters	51
Akaike (AIC)	12952.204
Bayesian (BIC)	13149.969
Sample-size adjusted Bayesian (BIC)	12988.173

Root Mean Square Error of Approximation:

RMSEA		0.052
90 Percent Confidence Interval	0.034	0.069
P-value RMSEA <= 0.05		0.406

Standardized Root Mean Square Residual:

SRMR	0.051
------	-------

Parameter Estimates:

Information	Expected
Information saturated (h1) model	Structured
Standard Errors	Standard

Latent Variables:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Time1 =~							
V1	(1a1)	0.977	0.080	12.258	0.000	0.928	0.729
V5		1.000				0.950	0.557
V9	(1a2)	1.108	0.095	11.670	0.000	1.053	0.844
Time2 =~							
V2	(1a1)	0.977	0.080	12.258	0.000	0.915	0.697
V6		1.000				0.937	0.494
V10	(1a2)	1.108	0.095	11.670	0.000	1.038	0.758
Time3 =~							
V3	(1a1)	0.977	0.080	12.258	0.000	1.014	0.726
V7		1.000				1.038	0.495
V11	(1a2)	1.108	0.095	11.670	0.000	1.150	0.807

.V10	0.191	0.083	2.316	0.021	0.191	0.319
.V11	0.118	0.078	1.526	0.127	0.118	0.210
.V12	0.117	0.078	1.507	0.132	0.117	0.192
.V10 ~~						
.V11	0.371	0.095	3.928	0.000	0.371	0.494
.V12	0.391	0.098	3.978	0.000	0.391	0.479
.V11 ~~						
.V12	0.358	0.108	3.306	0.001	0.358	0.467
Int ~~						
Growth	-0.041	0.022	-1.840	0.066	-0.213	-0.213

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Time1	0.000				0.000	0.000
Time2	0.000				0.000	0.000
Time3	0.000				0.000	0.000
Time4	0.000				0.000	0.000
Int	1.358	0.130	10.424	0.000	1.520	1.520
Growth	0.296	0.055	5.389	0.000	1.370	1.370
.V1	0.000				0.000	0.000
.V2	0.000				0.000	0.000
.V3	0.000				0.000	0.000
.V4	0.000				0.000	0.000
.V5	-0.499	0.142	-3.520	0.000	-0.499	-0.292
.V6	-0.430	0.168	-2.555	0.011	-0.430	-0.227
.V7	-0.629	0.202	-3.123	0.002	-0.629	-0.300
.V8	-0.656	0.228	-2.874	0.004	-0.656	-0.294
.V9	-0.954	0.135	-7.075	0.000	-0.954	-0.764
.V10	-0.936	0.163	-5.749	0.000	-0.936	-0.683
.V11	-1.265	0.196	-6.452	0.000	-1.265	-0.888
.V12	-1.550	0.225	-6.897	0.000	-1.550	-1.044

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.V1	0.761	0.089	8.581	0.000	0.761	0.469
.V2	0.884	0.099	8.893	0.000	0.884	0.514

.V3	0.921	0.111	8.314	0.000	0.921	0.472
.V4	0.911	0.115	7.923	0.000	0.911	0.460
.V5	2.008	0.169	11.904	0.000	2.008	0.690
.V6	2.723	0.223	12.200	0.000	2.723	0.756
.V7	3.320	0.270	12.299	0.000	3.320	0.755
.V8	3.857	0.311	12.388	0.000	3.857	0.775
.V9	0.449	0.093	4.819	0.000	0.449	0.288
.V10	0.800	0.114	6.988	0.000	0.800	0.426
.V11	0.707	0.123	5.732	0.000	0.707	0.348
.V12	0.832	0.135	6.143	0.000	0.832	0.377
Time1	0.105	0.048	2.208	0.027	0.116	0.116
Time2	0.115	0.034	3.421	0.001	0.131	0.131
Time3	0.205	0.044	4.608	0.000	0.190	0.190
Time4	0.022	0.058	0.377	0.706	0.019	0.019
Int	0.798	0.135	5.906	0.000	1.000	1.000
Growth	0.047	0.018	2.583	0.010	1.000	1.000

Defined Parameters:

	Estimate	Std.Err	z-value	$P(> z)$	Std.lv	Std.all
linear1	0.430	0.328	1.310	0.190	-1.495	-1.495
linear2	0.568	0.530	1.074	0.283	-2.272	-2.272

Output for Model 2 (Testing Linear Growth using LRT)

lavaan 0.6-3 ended normally after 77 iterations

Optimization method	NLMINB
Number of free parameters	55
Number of equality constraints	6
Number of observations	357
Estimator	ML
Model Fit Test Statistic	79.062
Degrees of freedom	41
P-value (Chi-square)	0.000

Model test baseline model:

Minimum Function Test Statistic	3173.220
Degrees of freedom	66
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.988
Tucker-Lewis Index (TLI)	0.980

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-6426.393
Loglikelihood unrestricted model (H1)	-6386.861
Number of free parameters	49
Akaike (AIC)	12950.785
Bayesian (BIC)	13140.794
Sample-size adjusted Bayesian (BIC)	12985.343

Root Mean Square Error of Approximation:

RMSEA		0.051
90 Percent Confidence Interval	0.034	0.068
P-value RMSEA <= 0.05		0.438

Standardized Root Mean Square Residual:

SRMR	0.050
------	-------

Parameter Estimates:

Information	Expected
Information saturated (h1) model	Structured
Standard Errors	Standard

Latent Variables:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Time1 =~							
V1	(1a)	0.973	0.080	12.229	0.000	0.916	0.723
V5		1.000				0.942	0.553
V9	(1b)	1.110	0.095	11.630	0.000	1.045	0.842
Time2 =~							
V2	(1a)	0.973	0.080	12.229	0.000	0.920	0.699
V6		1.000				0.946	0.498
V10	(1b)	1.110	0.095	11.630	0.000	1.049	0.762
Time3 =~							
V3	(1a)	0.973	0.080	12.229	0.000	1.010	0.724
V7		1.000				1.038	0.495
V11	(1b)	1.110	0.095	11.630	0.000	1.152	0.809
Time4 =~							
V4	(1a)	0.973	0.080	12.229	0.000	1.031	0.735
V8		1.000				1.060	0.475
V12	(1b)	1.110	0.095	11.630	0.000	1.177	0.791
Int =~							
Time1		1.000				0.954	0.954

Time2	1.000	0.951	0.951
Time3	1.000	0.866	0.866
Time4	1.000	0.848	0.848
Growth =~			
Time1	0.000	0.000	0.000
Time2	1.000	0.283	0.283
Time3	2.000	0.515	0.515
Time4	3.000	0.757	0.757

Covariances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.V1 ~~						
.V2	0.475	0.077	6.139	0.000	0.475	0.576
.V3	0.401	0.075	5.344	0.000	0.401	0.476
.V4	0.426	0.074	5.744	0.000	0.426	0.512
.V2 ~~						
.V3	0.513	0.085	6.031	0.000	0.513	0.568
.V4	0.406	0.084	4.827	0.000	0.406	0.453
.V3 ~~						
.V4	0.492	0.094	5.227	0.000	0.492	0.538
.V5 ~~						
.V6	1.453	0.161	9.020	0.000	1.453	0.622
.V7	1.265	0.167	7.577	0.000	1.265	0.490
.V8	1.159	0.174	6.655	0.000	1.159	0.416
.V6 ~~						
.V7	2.243	0.214	10.467	0.000	2.243	0.747
.V8	2.126	0.222	9.599	0.000	2.126	0.657
.V7 ~~						
.V8	2.842	0.260	10.931	0.000	2.842	0.794
.V9 ~~						
.V10	0.191	0.083	2.308	0.021	0.191	0.321
.V11	0.115	0.078	1.483	0.138	0.115	0.206
.V12	0.120	0.078	1.546	0.122	0.120	0.197
.V10 ~~						
.V11	0.366	0.095	3.841	0.000	0.366	0.491
.V12	0.383	0.099	3.853	0.000	0.383	0.472

.V11 ~~						
.V12	0.355	0.109	3.262	0.001	0.355	0.466
Int ~~						
Growth	-0.057	0.024	-2.321	0.020	-0.236	-0.236

Intercepts:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Time1	0.000				0.000	0.000
Time2	0.000				0.000	0.000
Time3	0.000				0.000	0.000
Time4	0.000				0.000	0.000
Int	1.351	0.129	10.445	0.000	1.504	1.504
Growth	0.355	0.037	9.713	0.000	1.327	1.327
.V1	0.000				0.000	0.000
.V2	0.000				0.000	0.000
.V3	0.000				0.000	0.000
.V4	0.000				0.000	0.000
.V5	-0.495	0.141	-3.503	0.000	-0.495	-0.291
.V6	-0.472	0.170	-2.775	0.006	-0.472	-0.248
.V7	-0.624	0.199	-3.130	0.002	-0.624	-0.297
.V8	-0.660	0.229	-2.888	0.004	-0.660	-0.296
.V9	-0.952	0.135	-7.063	0.000	-0.952	-0.767
.V10	-0.986	0.165	-5.962	0.000	-0.986	-0.716
.V11	-1.263	0.194	-6.504	0.000	-1.263	-0.887
.V12	-1.558	0.226	-6.900	0.000	-1.558	-1.047

Variances:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.V1	0.766	0.088	8.677	0.000	0.766	0.477
.V2	0.886	0.100	8.865	0.000	0.886	0.511
.V3	0.923	0.111	8.347	0.000	0.923	0.475
.V4	0.907	0.115	7.895	0.000	0.907	0.460
.V5	2.011	0.169	11.913	0.000	2.011	0.694
.V6	2.715	0.223	12.182	0.000	2.715	0.752
.V7	3.321	0.270	12.298	0.000	3.321	0.755
.V8	3.853	0.311	12.383	0.000	3.853	0.774

.V9	0.447	0.093	4.809	0.000	0.447	0.290
.V10	0.793	0.115	6.868	0.000	0.793	0.419
.V11	0.702	0.124	5.663	0.000	0.702	0.346
.V12	0.830	0.136	6.084	0.000	0.830	0.375
Time1	0.079	0.045	1.749	0.080	0.089	0.089
Time2	0.128	0.034	3.814	0.000	0.143	0.143
Time3	0.211	0.043	4.848	0.000	0.196	0.196
Time4	0.014	0.049	0.276	0.783	0.012	0.012
Int	0.808	0.137	5.918	0.000	1.000	1.000
Growth	0.072	0.015	4.688	0.000	1.000	1.000

Model Comparisons

Chi Square Difference Test

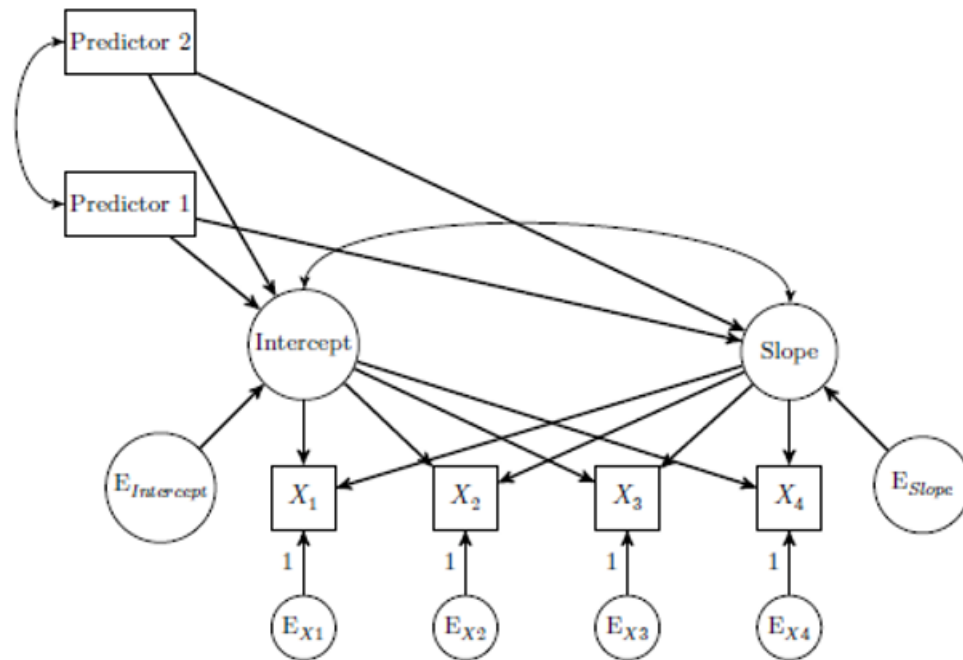
	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
fit1	39	12952	13150	76.481			
fit2	41	12951	13141	79.062	2.5812	2	0.2751

8.9. LGM with Covariates

8.9.1. Models with Time-Invariant Covariates

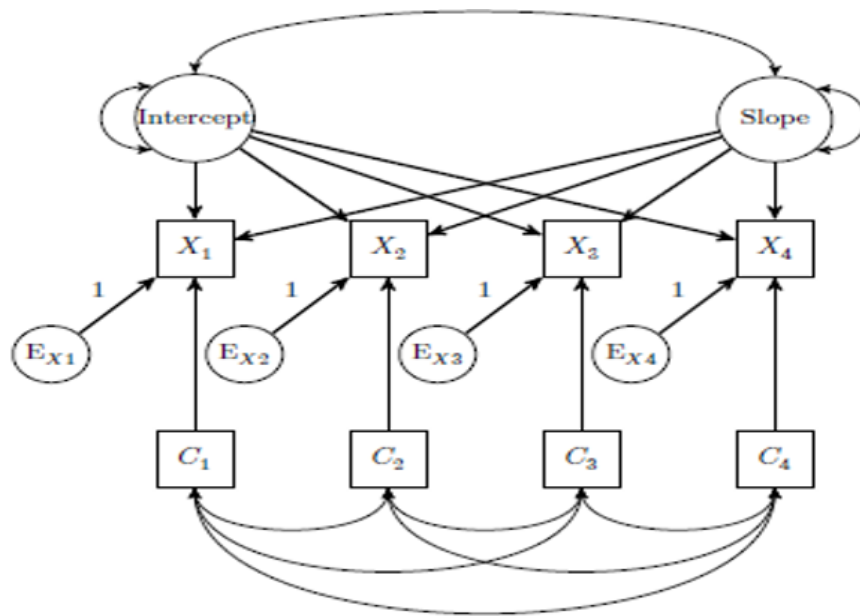
- Time-invariant covariates are stable measures over all the data collection time periods.
- Examples are number of siblings, socioeconomic status.

- The following is a 4-point LGM model with 2 time-invariant covariates, Predictor 1 and Predictor 2 (Beaujean, 2014; Figure 5.3a):



8.9.2 Models with Time-Dependent Covariates

- Time-dependent covariates vary with time.
- Examples are investment return, mood, blood pressure.
- The following is a 4-point LGM model one time-dependent covariate, C (Beaujean, 2014; Figure 5.3b):



8.10. Limitations

- Balanced-on-time design (Ware, 1985)
 - equal number of observations for all individuals
 - equal spacing of assessments for all individuals