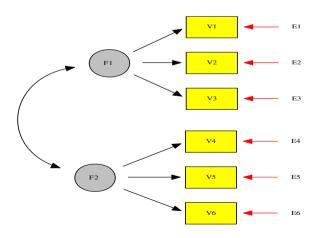
# 4 Structural Equation Modeling 1: Path Analysis

# **References:**

• Beaujean (2014). Chapter 2.

# **4.1. Why SEM?**

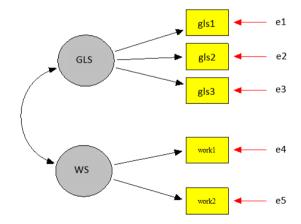
- 1. Confirmatory factor analysis
- SEM examines how well the observed variables measure the underlying constructs



• Example 1. The Subjective Well Being Model

• Filename: swb.cov (N = 500)

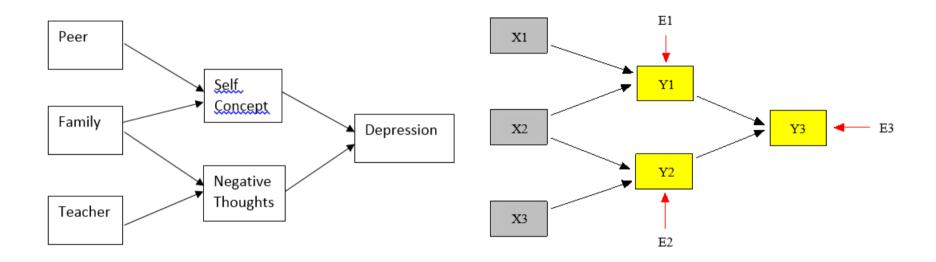
	V1	V2	V3	V4	V5
V1 (gls1)	198				
V2 (gls2)	82	86			
V3 (gls3)	54	28	24		
V4 (work1)	52	30	18	151	
V5 (work2)	16	10	7	44	28



• See lecture notes in Chapter 3 for details

# 2. Path analysis

• SEM examines the relationship among a set of observed variables

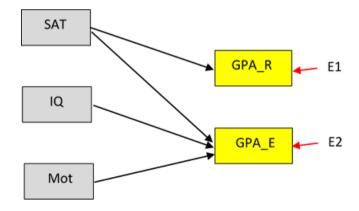


• Extension of multiple regression analysis

- Example 2. College Academic Performance (Raykov, 2006)
- Filename: college.cov (N = 150)

	GPA_R	GPA_E	SAT	IQ	Motiv
GPA_R	.594				
GPA_E	.483	.754			
SAT	3.993	3.626	47.457		
IQ	.426	1.757	4.100	10.267	
Motiv	.500	.722	6.394	.525	2.675

GPA\_R=GPA in required courses, GPA\_E=GPA in elective courses, SAT=Scholastic aptitude test, IQ=intelligence score, Motiv=motivation



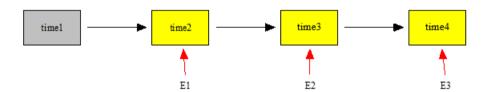
# • Example 3. Profit Growth

• Filename: profit.cov (N = 200 companies)

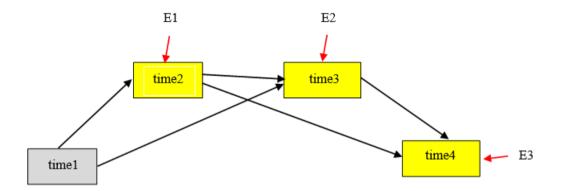
	time1	time2	time3	time4	
time1	40				
time2	37	53			
time3	40	48	60		
time4	50	63	70	107	

time1=profit at time 1, time2=profit at time 2, time3=profit at time 3, time4=profit at time 4

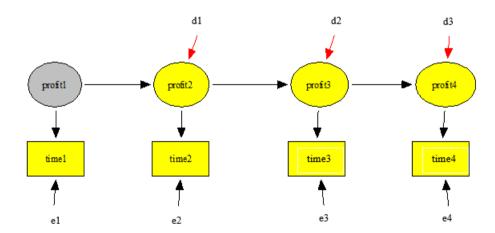
# • Model 1: First-order model



# • Model 2: Second-order model

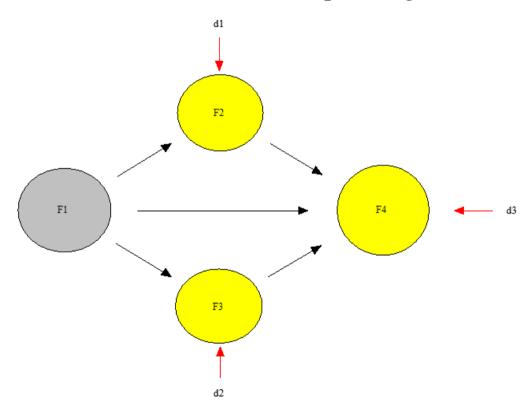


# • Model 3: Latent variable model



# 3. Latent variable analysis

• SEM examines the relationship among a set of latent constructs



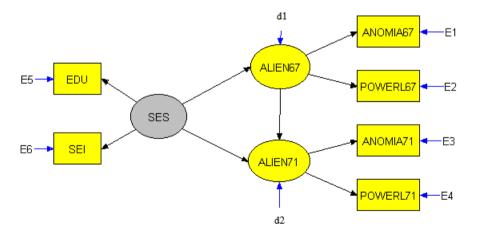
• Combining CFA (measurement model) and path analysis (with latent variables)

• Example 4. Stability of Alienation (Wheaton et al., 1977)

• Filename: alien.cov (N = 932)

	ANOMIA67	POWERL67	ANOMIA71	POWERL71	<b>EDUC</b>	SEI
ANOMIA67	11.83					
POWERL67	6.95	9.36				
ANOMIA71	6.82	5.09	12.53			
POWERL71	4.78	5.03	7.50	9.99		
EDUC	-3.84	-3.89	-3.84	-3.63	9.61	
SEI	-2.19	-1.88	-2.72	-1.88	3.55	4.50

ANOMIA67, ANOMIA71=a scale measured anomia in 1967 and 1971 POWERL67, POWERL71=a scale measured powerlessness in 1967 and 1971 EDUC=education level, SEI=socioeconomic index



# 4.2. Path Analysis

- Suppose there is a set of p variables (y, x) with a covariance matrix  $\Sigma$ . The *structural model* represents our belief about how  $\Sigma$  is structured. That is,  $\Sigma = \Sigma(\theta)$ .
- Basic tasks involve
  - parameter estimation
  - model evaluation
  - model modification
- We follow the same 5-step procedure as in CFA

# **4.3.** Model Specification

# • Model equation:

$$y = \mu_y + \beta y + \gamma x + e$$
$$x = \mu_x + (x - \mu_x)$$

y is  $p_y \times 1$  vector of observed dependent variables x is  $p_x \times 1$  vector of observed independent variables  $\mu_y$  is  $p_y \times 1$  vector of intercepts of y  $\beta$  is  $p_y \times p_y$  matrix of path coefficients among the y variables  $\gamma$  is  $p_y \times p_x$  matrix of path coefficients from x to y e is  $p_y \times 1$  vector of measurement errors  $\mu_x = E(x)$  is  $p_x \times 1$  vector of means of x

• Combining the observed variables y and x, we have

$$\begin{bmatrix} y \\ x \end{bmatrix} = \begin{bmatrix} \mu_y \\ \mu_x \end{bmatrix} + \begin{bmatrix} \beta & \gamma \\ 0 & 0 \end{bmatrix} \begin{bmatrix} y \\ x \end{bmatrix} + \begin{bmatrix} e \\ x - \mu_x \end{bmatrix}$$

$$v = \mu + Bv + z$$

• Covariance matrix of *v* is

$$\Sigma = \text{cov}\{(I - B)^{-1}(\mu + z)\}\$$

$$= (I - B)^{-1}\Psi(I - B)^{-1'}$$

$$= \Sigma(\theta)$$

where B is the  $p \times p$  path coefficient matrix, and  $\Psi$  is the  $p \times p$  variance-covariance matrix of e and x.

• In path analysis, the variables are:

Name	Type	Cause/Effect	Dimension
y	observed	DV	$p_{\mathrm{y}} \times 1$
$\mathcal{X}$	observed	IV	$p_x \times 1$
e	latent	IV	$p_{ m v}  imes 1$

• And the parameter matrices are:

Parameter matrix	Symbol	Name	Dimension
path coefficients among	B	beta	$p \times p$
the observed variables			
variance-covariance	$\Psi$	psi	$p \times p$
matrix of $e$ and $x$			

# 4.4. Identification

- The model  $\Sigma = \Sigma(\theta)$  is *identified* if there are no vectors  $\theta^*$  and  $\theta$  such that  $\Sigma(\theta^*) = \Sigma(\theta)$  unless  $\theta^* = \theta$
- ULI and UVI are irrelevant
- The *t*-rule remains valid (necessary condition for identification)

# 4.5. Estimation

• Estimation methods are basically the same as that in §3.6

# 4.6. Goodness of Fit Assessment

• Same as that in §3.7

```
filename: college.R
# Example 2: College Academic Performance (Raykov, 2006)
# set work directory
setwd("c:/users/wchan/google drive/stat6108/data")
# load the lavaan package
library(lavaan)
data <- scan("college.cov")</pre>
# write the input data into a full covariance matrix
college.cov <- getCov(data, names=c("GPA_R", "GPA_E", "SAT", "IQ", "Motiv"))</pre>
# Specify Model 1
college1.model <- "</pre>
# regression equation (B)
GPA R ~ SAT
GPA E ~ SAT + IO + Motiv
# error variance of e (psi)
GPA_R ~~ GPA_R
GPA E ~~ GPA E
# variance-covariance of x (psi)
SAT ~~ SAT
IQ ~~ IQ
Motiv ~~ Motiv
SAT ~~ IO + Motiv
IO ~~ Motiv
# Fit Model 1 to the data
fit1 <- lavaan(college1.model, sample.cov=college.cov, sample.nobs=150, fixed.x=FALSE)
mi1 <- modindices(fit1, sort.=TRUE)</pre>
```

```
# Specify Model 2 (based on modification indices from Model 1)
college2.model <- "
# Regression Equation (B)
GPA R ~ SAT
GPA E ~ SAT + IQ + Motiv
# variance-covariance of x (psi)
SAT ~~ SAT
IQ ~~ IQ
Motiv ~~ Motiv
SAT ~~ IO + Motiv
IQ ~~ Motiv
# error Variance and Covariance (psi)
GPA R ~~ GPA R
GPA E ~~ GPA E
GPA R ~~ GPA E
# Fit Model 2 to the data
fit2 <- lavaan(college2.model, sample.cov=college.cov, sample.nobs=150, fixed.x=FALSE)
mi2 <- modindices(fit2, sort.=TRUE)</pre>
sink("college.out", split=TRUE)
writeLines("\n Example 2: College Academic Performance (Raykov, 2006) \n")
writeLines("\n Output for Model 1 \n")
writeLines("\n Sample covariance matrix \n")
list(college.cov)
writeLines("\n residual matrix \n")
residuals(fit1, type="raw")
writeLines("\n standardized residual matrix \n")
residuals(fit1, type="cor")
writeLines("\n free parameters in Model 1 \n")
inspect(fit1)
```

```
summary(fit1, fit.measures=TRUE, standardized=TRUE, rsquare=TRUE)
writeLines("\n modification indices \n")
list(mi1)
writeLines("\n Output for Model 2 \n")
writeLines("\n residual matrix \n")
residuals(fit2, type="raw")
writeLines("\n standardized residual matrix \n")
residuals(fit2, type="cor")
writeLines("\n free parameters in Model 2 \n")
inspect(fit2)
summary(fit2, fit.measures=TRUE, standardized=TRUE, rsquare=TRUE)
writeLines("\n modification indices \n")
list(mi2)
writeLines("\n Comparing Model 1 and Model 2 \n")
lavTestLRT(fit1, fit2)
sink()
```

```
filename: college.out
 Example 2: College Academic Performance (Raykov, 2006)
 Output for Model 1
 Sample covariance matrix
[[1]]
     GPA R GPA E
                    SAT
                            IQ Motiv
GPA R 0.594 0.483 3.993 0.426 0.500
GPA_E 0.483 0.754 3.626 1.757 0.722
SAT 3.993 3.626 47.457 4.100 6.394
     0.426 1.757 4.100 10.267 0.525
IO
Motiv 0.500 0.722 6.394 0.525 2.675
 residual matrix
$type
[1] "raw"
$cov
     GPA_R GPA_E SAT
                          IQ
                                Motiv
GPA R 0.000
GPA_E 0.177 0.000
      0.000 0.000 0.000
SAT
      0.080 0.000 0.000 0.000
IQ
Motiv -0.038 0.000 0.000 0.000 0.000
 standardized residual matrix
$type
[1] "cor.bollen"
$cov
```

```
GPA_R GPA_E SAT
                       ΙQ
                             Motiv
GPA_R 0.000
GPA_E 0.266 0.000
      0.000 0.000 0.000
SAT
ΙQ
      0.033 0.000 0.000 0.000
Motiv -0.030 0.000 0.000 0.000 0.000
free parameters in Model 1
$lambda
     GPA_R GPA_E SAT IQ Motiv
              0
                 0 0
GPA R
GPA E
              0
                 0 0
           0 0 0
SAT
        0
              0 0 0
ΙQ
Motiv
        0
              0 0 0
$theta
     GPA_R GPA_E SAT IQ Motiv
GPA R 0
GPA E 0
SAT 0
          0 0 0 0 0
     0
IQ
Motiv 0
$psi
     GPA_R GPA_E SAT IQ Motiv
GPA_R 5
GPA E 0
               7
SAT
    0
               10
ΙQ
                   8
Motiv 0
               11 12 9
```

\$beta

	GPA_R	GPA_E	SAT	ΙQ	Motiv
GPA_R	0	0	1	0	0
GPA_E	0	0	2	3	4
SAT	0	0	0	0	0
IQ	0	0	0	0	0
Motiv	0	0	0	0	0

### lavaan 0.6-5 ended normally after 52 iterations

Estimator	ML
Optimization method	NLMINB
Number of free parameters	12

Number of observations 150

#### Model Test User Model:

Test statistic	100.104
Degrees of freedom	3
P-value (Chi-square)	0.000

### Model Test Baseline Model:

Test statistic	463.244
Degrees of freedom	10
P-value	0.000

### User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.786
Tucker-Lewis Index (TLI)	0.286

### Loglikelihood and Information Criteria:

Loglikelihood user model	(HO)	-1357.836
--------------------------	------	-----------

Loglikelihood u	nrestricted	model (H	1) -	1307.784		
Akaike (AIC)				2739.672		
Bayesian (BIC)				2775.799		
Sample-size adj	usted Bayes	ian (BIC)		2737.822		
	-					
Root Mean Square	Error of Ap	proximati	on:			
RMSEA				0.465		
90 Percent conf	idence inte	rval - lo	wer	0.389		
90 Percent conf	idence inte	rval - up	per	0.545		
P-value RMSEA <		•	•	0.000		
Standardized Root	Mean Squar	e Residua	1:			
SRMR				0.070		
Dium				0.070		
Parameter Estimat	es:					
Information				Expected		
Information sat	urated (h1)	model		ructured		
Standard errors	• •			Standard		
33411414 311313						
Regressions:						
•	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
GPA_R ~						
SAT	0.084	0.006	13.975	0.000	0.084	0.752
GPA_E ~						
SAT	0.046	0.007	6.523	0.000	0.046	0.366
IQ	0.146	0.013	11.599	0.000	0.146	0.539
Motiv	0.131	0.029	4.449	0.000	0.131	0.247
Covariances:						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
SAT ~~						

<b>T</b> 0	4 070	1 001	0 007	0 005	4 070	0 100
IQ	4.073	1.821	2.237	0.025	4.073	0.186
Motiv	6.351	1.051	6.045	0.000	6.351	0.567
IQ ~~						
Motiv	0.521	0.427	1.221	0.222	0.521	0.100
Variances:						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
.GPA_R	0.256	0.030	8.660	0.000	0.256	0.434
.GPA_E	0.234	0.027	8.660	0.000	0.234	0.312
SAT	47.141	5.443	8.660	0.000	47.141	1.000
IQ	10.199	1.178	8.660	0.000	10.199	1.000
Motiv	2.657	0.307	8.660	0.000	2.657	1.000

### R-Square:

GPA\_R 0.566 GPA\_E 0.688

#### modification indices

#### [[1]]

lhs op rhs epc sepc.lv sepc.all sepc.nox mi 23 GPA\_E ~ GPA\_R 72.199 0.663 0.663 0.588 0.588 13 GPA\_R ~~ GPA\_E 72.199 0.170 0.694 0.694 0.170 20 GPA\_R ~ GPA\_E 38.579 0.373 0.373 0.420 0.420 22 GPA R ~ Motiv 0.463 -0.021 -0.021 -0.044-0.04432 Motiv ~ GPA\_R 0.457 -0.146 -0.146 -0.069 -0.069 16 GPA\_R ~~ Motiv 0.457 -0.038 -0.038-0.045-0.04521 GPA\_R ~ IQ 0.385 0.008 0.008 0.034 0.034 15 GPA\_R ~~ IQ 0.380 0.080 0.080 0.049 0.049 IQ ~ GPA\_R 0.380 0.312 0.312 0.075 28 0.075 0.084 24 SAT ~ GPA R 0.238 0.755 0.755 0.084 14 GPA\_R ~~ SAT 0.238 0.194 0.194 0.056 0.056

```
Output for Model 2
```

residual matrix

\$type

[1] "raw"

\$cov

GPA\_R GPA\_E SAT IQ Motiv
GPA\_R 0.000
GPA\_E 0.006 0.008
SAT 0.000 0.000
IQ 0.080 0.054 0.000 0.000
Motiv -0.038 -0.025 0.000 0.000 0.000

standardized residual matrix

\$type

[1] "cor.bollen"

\$cov

GPA\_R GPA\_E SAT IQ Motiv

GPA\_R 0.000

GPA\_E 0.005 0.000

SAT 0.000 -0.003 0.000

IQ 0.033 0.016 0.000 0.000

Motiv -0.030 -0.021 0.000 0.000 0.000

free parameters in Model 2

\$lambda

```
GPA E
                  0 0
                          0
                  0 0
SAT
                          0
ΙQ
                  0 0
                  0 0
Motiv
$theta
     GPA_R GPA_E SAT IQ Motiv
GPA_R 0
GPA E 0
SAT 0
ΙQ
         0
             0 0
0 0 0
     0
Motiv 0
$psi
     GPA_R GPA_E SAT IQ Motiv
GPA R 11
GPA_E 13
          12
          0
SAT
    0
                 5
ΙQ
                   6
                 9 10 7
Motiv 0
$beta
     GPA_R GPA_E SAT IQ Motiv
GPA R
                  1 0
         0
                  2 3
GPA_E
         0
SAT
                  0 0
         0
              0
ΙQ
         0
                  0 0
                          0
                  0 0
```

Motiv

lavaan 0.6-5 ended normally after 62 iterations

Estimator	ML
Optimization method	NLMINB
Number of free parameters	13

0

Number of observations	150
Model Test User Model:	
Test statistic	0.845
Degrees of freedom P-value (Chi-square)	2 0.656
Model Test Baseline Model:	
Test statistic	463.244 10
Degrees of freedom P-value	0.000
User Model versus Baseline Model:	
Comparative Fit Index (CFI)	1.000
Tucker-Lewis Index (TLI)	1.013
Loglikelihood and Information Criteria:	
Loglikelihood user model (H0)	-1308.206
Loglikelihood unrestricted model (H1)	-1307.784
Akaike (AIC)	2642.412
Bayesian (BIC)	2681.550
Sample-size adjusted Bayesian (BIC)	2640.408
Root Mean Square Error of Approximation:	
RMSEA	0.000
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.126
P-value RMSEA <= 0.05	0.745

# Standardized Root Mean Square Residual:

SRMR	0.014

0.256

### Parameter Estimates:

.GPA\_R

Information Expected						
Information sat	urated (h1)	model	St	ructured		
Standard errors				Standard		
_						
Regressions:	<b>=</b>	0.15	. 1	54.1.13	G1 1 1	G1 1 11
GD3 D	Estimate	Sta.Err	z-value	P(> Z )	Sta.IV	Std.all
GPA_R ~						
SAT	0.084	0.006	13.975	0.000	0.084	0.752
GPA_E ~						
SAT		0.006				
IQ	0.141	0.009	15.550	0.000	0.141	0.522
Motiv	0.145	0.021	6.851	0.000	0.145	0.274
Covariances:						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
SAT ~~						
IQ	4.073	1.821	2.237	0.025	4.073	0.186
Motiv	6.351	1.051	6.045	0.000	6.351	0.567
IQ ~~						
Motiv	0.522	0.427	1.221	0.222	0.522	0.100
.GPA_R ~~						
. GPA_E	0.171	0.024	7.001	0.000	0.171	0.697
Variances:						
	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
SAT	47.141			0.000		
IQ	10.199			0.000		
Motiv	2.657		8.660	0.000		1.000
1-10 C T A	2.057	0.507	0.000	0.000	2.007	1.000

0.030

8.660

0.000

0.256

0.434

```
0.235
                              0.027
                                      8.660
                                                        0.235
                                                                 0.317
   .GPA E
                                               0.000
R-Square:
                  Estimate
                     0.566
    GPA R
   GPA E
                     0.683
 modification indices
[[1]]
                          epc sepc.lv sepc.all sepc.nox
    lhs op
             rhs
                    mi
22 GPA_R ~ Motiv 0.463 -0.021 -0.021
                                       -0.044
                                                -0.044
16 GPA R ~~ Motiv 0.457 -0.038 -0.038
                                       -0.045
                                                -0.045
33 Motiv ~ GPA E 0.457 -0.220 -0.220
                                       -0.116
                                                -0.116
32 Motiv ~ GPA R 0.457 -0.146 -0.146
                                       -0.069
                                                -0.069
21 GPA R ~
              IO 0.385 0.008
                                0.008
                                        0.034
                                                 0.034
                                                 0.049
              IQ 0.380 0.080
15 GPA R ~~
                                0.080
                                        0.049
28
     IO ~ GPA R 0.380 0.312
                                0.312
                                        0.075
                                                 0.075
     IO ~ GPA E 0.380 0.468
                                0.468
                                         0.126
                                                 0.126
29
25 SAT ~ GPA E 0.238 1.133
                                1.133
                                         0.142
                                                 0.142
14 GPA R ~~
             SAT 0.238 0.194
                                0.194
                                         0.056
                                                 0.056
    SAT ~ GPA R 0.238 0.755
                                0.755
                                         0.084
                                                 0.084
```

0.025

0.028

0.028

#### Comparing Model 1 and Model 2

20 GPA R ~ GPA E 0.087 0.025

#### Chi-Squared Difference Test

```
Df AIC BIC Chisq Chisq diff Df diff Pr(>Chisq)
fit2 2 2642.4 2681.6 0.8445
fit1 3 2739.7 2775.8 100.1044 99.26 1 < 2.2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

Example 2. College Academic Performance

Model T df p NNFI CFI RMSEA SRMR  $\Delta \chi^2(\Delta df)$  p

```
filename: profit.R
# Example 3: Profit Growth
# set work directory
setwd("c:/users/wchan/google drive/stat6108/data")
# load the lavaan package
library(lavaan)
ability <- scan("profit.cov")</pre>
# write the input data into a full covariance matrix
ability.cov <- getCov(ability, names=c("time1", "time2", "time3", "time4"))
# specify Model 1 (first order model)
model1 <- "
# regression Equation (Beta)
time2 ~ time1
time3 ~ time2
time4 ~ time3
# Variance of x (Psi)
time1 ~~ time1
# error variance (Psi)
time2 ~~ time2
time3 ~~ time3
time4 ~~ time4
# specify Model 2 (second order model)
model2 <- "
# regression Equation (Beta)
time2 ~ time1
time3 ~ time1 + time2
```

```
time4 ~ time2 + time3
# Variance of x (Psi)
time1 ~~ time1
# error variance (Psi)
time2 ~~ time2
time3 ~~ time3
time4 ~~ time4
# specify Model 3 (first order model with latent variables)
model3 <- "
# measurement equations (Lambda)
Profit1 =~ 1*time1
Profit2 =~ 1*time2
Profit3 =~ 1*time3
Profit4 =~ 1*time4
# structural equations (Beta)
Profit2 ~ Profit1
Profit3 ~ Profit2
Profit4 ~ Profit3
# constraining error variances (Theta)
time1 ~~ vare*time1
time2 ~~ vare*time2
time3 ~~ vare*time3
time4 ~~ vare*time4
# Fit Models 1-3 to the data
fit1 <- lavaan (model1, sample.cov=ability.cov, sample.cov.rescale=FALSE, sample.nobs=200, fixed.x=FALSE)
fit2 <- lavaan (model2, sample.cov=ability.cov, sample.cov.rescale=FALSE, sample.nobs=200, fixed.x=FALSE)
fit3 <- lavaan (model3, sample.cov=ability.cov, sample.cov.rescale=FALSE, sample.nobs=200, auto.var=TRUE)
```

```
# save the output
sink("profit.out", split=TRUE)
writeLines("\n Example 3: Profit Growth\n")
writeLines("\n Output for Model 1\n")
inspect(fit1)
summary(fit1, fit.measures=TRUE, standardized=TRUE, rsquare=TRUE)
writeLines("\n Output for Model 2\n")
inspect(fit2)
summary(fit2, fit.measures=TRUE, standardized=TRUE, rsquare=TRUE)
lavTestLRT(fit1, fit2)
writeLines("\n Output for Model 3\n")
inspect(fit3)
summary(fit3, fit.measures=TRUE, standardized=TRUE, rsquare=TRUE)
sink()
```

```
filename: profit.out
 Example 3: Profit Growth
 Output for Model 1
$lambda
      time2 time3 time4 time1
time2
          0
                      0
                            0
time3
          0
                0
                      0
time4
                            0
                      0
time1
                            0
$theta
      time2 time3 time4 time1
time2 0
time3 0
time4 0
                  0
time1 0
            0
                  0
                        0
$psi
      time2 time3 time4 time1
time2 5
time3 0
time4 0
                  0
time1 0
$beta
      time2 time3 time4 time1
          0
                0
                      0
time2
                            0
time3
                0
                      0
time4
                3
                      0
                            0
          0
time1
                0
                      0
          0
                            0
```

lavaan 0.6-5 ended normally after 16 iterations

Estimator Optimization method Number of free parameters	ML NLMINB 7
Number of observations	200
Model Test User Model:	
Test statistic Degrees of freedom P-value (Chi-square)	68.771 3 0.000
Model Test Baseline Model:	
Test statistic Degrees of freedom P-value	822.319 6 0.000
User Model versus Baseline Model:	
Comparative Fit Index (CFI) Tucker-Lewis Index (TLI)	0.919 0.839
Loglikelihood and Information Criteria:	
Loglikelihood user model (H0) Loglikelihood unrestricted model (H1)	-2401.011 -2366.626
Akaike (AIC) Bayesian (BIC) Sample-size adjusted Bayesian (BIC)	4816.022 4839.110 4816.933
Root Mean Square Error of Approximation:	
RMSEA	0.331

90 Percent confidence interval - lower	0.266
90 Percent confidence interval - upper	0.401
P-value RMSEA <= 0.05	0.000

### Standardized Root Mean Square Residual:

SRMR 0.073

### Parameter Estimates:

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

# Regressions:

	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
time2 ~						
time1	0.925	0.048	19.094	0.000	0.925	0.804
time3 ~						
time2	0.906	0.039	22.935	0.000	0.906	0.851
time4 ~						
time3	1.167	0.046	25.392	0.000	1.167	0.874
Variances:						
	Fetimato	Std Err	7-172 1 110	D (> - 1	S+4 157	11c h+2

timel	40.000	4.000	10.000	0.000	40.000	1.000
.time2	18.775	1.877	10.000	0.000	18.775	0.354
.time3	16.528	1.653	10.000	0.000	16.528	0.275
.time4	25.333	2.533	10.000	0.000	25.333	0.237

### R-Square:

.mate
. 646
.725
.763
'

### Output for Model 2

#### \$lambda

	time2	time3	time4	time1
time2	0	0	0	0
time3	0	0	0	0
time4	0	0	0	0
time1	0	0	0	0

#### \$theta

time2 time3 time4 time1 time2 0 time3 0 0 time4 0 0 0 time1 0 0 0 0

### \$psi

time2 time3 time4 time1 time2 7 time3 0 8 time4 0 0 9 time1 0 0 6

#### \$beta

time2 time3 time4 time1 time2 0 0 0 1 1 time3 3 0 0 2 2 time4 4 5 0 0 0 time1 0 0 0

### lavaan 0.6-5 ended normally after 20 iterations

Estimator ML
Optimization method NLMINB
Number of free parameters 9

Number of observations	200
Model Test User Model:	
Test statistic	0.687
Degrees of freedom P-value (Chi-square)	1 0.407
Model Test Baseline Model:	
Test statistic	822.319
Degrees of freedom P-value	6 0.000
User Model versus Baseline Model:	
Comparative Fit Index (CFI)	1.000
Tucker-Lewis Index (TLI)	1.002
Loglikelihood and Information Criteria:	
Loglikelihood user model (H0)	-2366.969
Loglikelihood unrestricted model (H1)	-2366.626
Akaike (AIC)	4751.939
Bayesian (BIC)	4781.623
Sample-size adjusted Bayesian (BIC)	4753.110
Root Mean Square Error of Approximation:	
RMSEA	0.000
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.175
P-value RMSEA <= 0.05	0.514

# Standardized Root Mean Square Residual:

SRMR 0.005

### Parameter Estimates:

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

# Regressions:

•	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
time2 ~						
time1	0.925	0.048	19.094	0.000	0.925	0.804
time3 ~						
time1	0.458	0.069	6.623	0.000	0.458	0.374
time2	0.586	0.060	9.751	0.000	0.586	0.551
time4 ~						
time2	0.479	0.087	5.527	0.000	0.479	0.337
time3	0.783	0.082	9.604	0.000	0.783	0.586
Variances:						

	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
time1	40.000	4.000	10.000	0.000	40.000	1.000
.time2	18.775	1.877	10.000	0.000	18.775	0.354
.time3	13.555	1.356	10.000	0.000	13.555	0.226
.time4	21.977	2.198	10.000	0.000	21.977	0.205

# R-Square:

	Estimate
time2	0.646
time3	0.774
time4	0.795

### Chi-Squared Difference Test

Df AIC BIC Chisq Chisq diff Df diff Pr(>Chisq)
fit2 1 4751.9 4781.6 0.6874
fit1 3 4816.0 4839.1 68.7706 68.083 2 1.644e-15 \*\*\*

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

```
Output for Model 3
```

Note: model contains equality constraints:

### \$lambda

	Proftl	Proft2	Proft3	Proft4
time1	0	0	0	0
time2	0	0	0	0
time3	0	0	0	0
time4	0	0	0	0

#### \$theta

time1 time2 time3 time4

time1 4 time2 0 5 time3 0 0 6 time4 0 0 0 7

### \$psi

Proft1 Proft2 Proft3 Proft4

Profit1 8
Profit2 0 9
Profit3 0 0 10
Profit4 0 0 0 11

### \$beta

	Proft1	Proft2	Proft3	Proft4
Profit1	0	0	0	0
Profit2	1	0	0	0
Profit3	0	2	0	0

Profit4	0	0	3	0	
lavaan 0.6-5	ended	normally	after	54	iterations

lavaan 0.6-5 ended normally after 54 fterations	
Estimator	ML
Optimization method	NLMINB
Number of free parameters	11
Number of equality constraints	3
Row rank of the constraints matrix	3
Number of observations	200
Model Test User Model:	
Test statistic	4.397
Degrees of freedom	2
P-value (Chi-square)	0.111
Model Test Baseline Model:	
Mont obstickin	000 010

# M

Test statistic	822.319
Degrees of freedom	6
P-value	0.000

# User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.997
Tucker-Lewis Index (TLI)	0.991

# Loglikelihood and Information Criteria:

Loglikelihood user model (H0) Loglikelihood unrestricted model	(H1)	-2368.824 -2366.626
Akaike (AIC)		4753.648

Bayesian (BIC) Sample-size adju	usted Bayes	ian (BIC)		4780.034 4754.689		
Root Mean Square I	Error of Ap	proximati	on:			
RMSEA 90 Percent conf: 90 Percent conf: P-value RMSEA <=	idence inte			0.077 0.000 0.178 0.234		
Standardized Root	Mean Squar	e Residua	1:			
SRMR				0.008		
Parameter Estimate	es:					
Information Information satu Standard errors	urated (h1)	model		Expected ructured Standard		
Latent Variables:			_			
Profit1 =~	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
time1	1.000				5.767	0.912
Profit2 =~ time2	1.000				6.782	0.934
Profit3 =~ time3	1.000				7.317	0.942
Profit4 =~ time4	1.000				10.013	0.968
Regressions:						
	Estimate	Std.Err	z-value	P(> z )	$\mathtt{Std.lv}$	Std.all

0.065 17.247

0.000

0.952

0.952

1.120

Profit2 ~ Profit1

Profit3 ~							
Profit2		1.050	0.046	22.710	0.000	0.973	0.973
Profit4 ~							
Profit3		1.303	0.054	24.205	0.000	0.952	0.952
Variances:							
		Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
.time1	(vare)	6.737	0.881	7.644	0.000	6.737	0.168
.time2	(vare)	6.737	0.881	7.644	0.000	6.737	0.128
.time3	(vare)	6.737	0.881	7.644	0.000	6.737	0.112
.time4	(vare)	6.737	0.881	7.644	0.000	6.737	0.063
Profit1		33.263	4.096	8.121	0.000	1.000	1.000
.Profit2		4.294	2.048	2.097	0.036	0.093	0.093
.Profit3		2.863	1.433	1.998	0.046	0.053	0.053
.Profit4		9.377	2.625	3.572	0.000	0.094	0.094

# R-Square:

	Estimate
time1	0.832
time2	0.872
time3	0.888
time4	0.937
Profit2	0.907
Profit3	0.947
Profit4	0.906

Example 3. Profit Growth

Model T df p NNFI CFI RMSEA SRMR  $\Delta \chi^2(\Delta df)$  p AIC