

# Confirmatory factor analysis

The measurement model

# Definitions

- Confirmatory factor analysis
  - SEM without causal paths among latent variables
- Exploratory factor analysis (EFA)
  - Principal components analysis (PCA)
  - Principal factor analysis (PFA)
- Path analysis
  - SEM without latent variables
- Structural equation modeling (SEM)
  - I reserve this terms for models with latent variables and causal paths

# CFA

- The null hypothesis for model fit
  - The observed variance/covariance matrix is equal to the variance/covariance matrix implied by the model
  - $H_0 : R_{vv} = R'_{vv}$
  - $H_0 : \Sigma = \Sigma(\theta)$ 
    - $\Sigma$  is the variance/covariance matrix
    - $\Theta$  is vector, containing the free parameters

# CFA

- The null hypothesis for model fit
  - Evaluated with a chi-square test
  - If chi-square is significant then the model does not fit
    - Observed variance/covariance matrix is independent from the implied variance/covariance matrix
    - In short, significance is “bad”

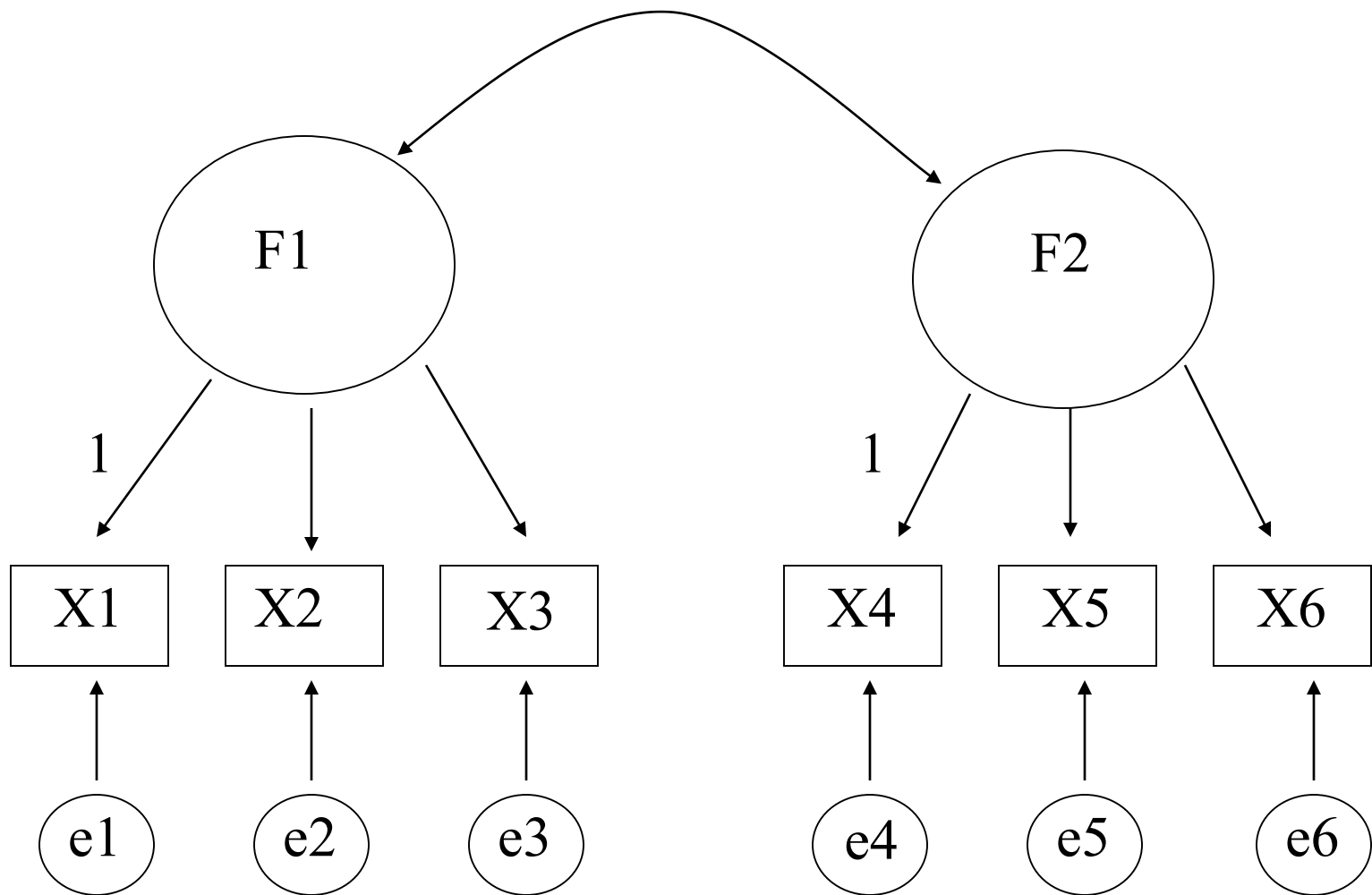
# CFA

- The null hypothesis for model fit
  - Can also compare the fit of two models, e.g., 1-factor (model 1) vs. 2-factor (model 2)
    - $\chi^2(\text{model 1}) - \chi^2(\text{model 2})$
    - $df(\text{model 1}) - df(\text{model 2})$
  - Can also compare models by comparing various fit indices (more on this later)

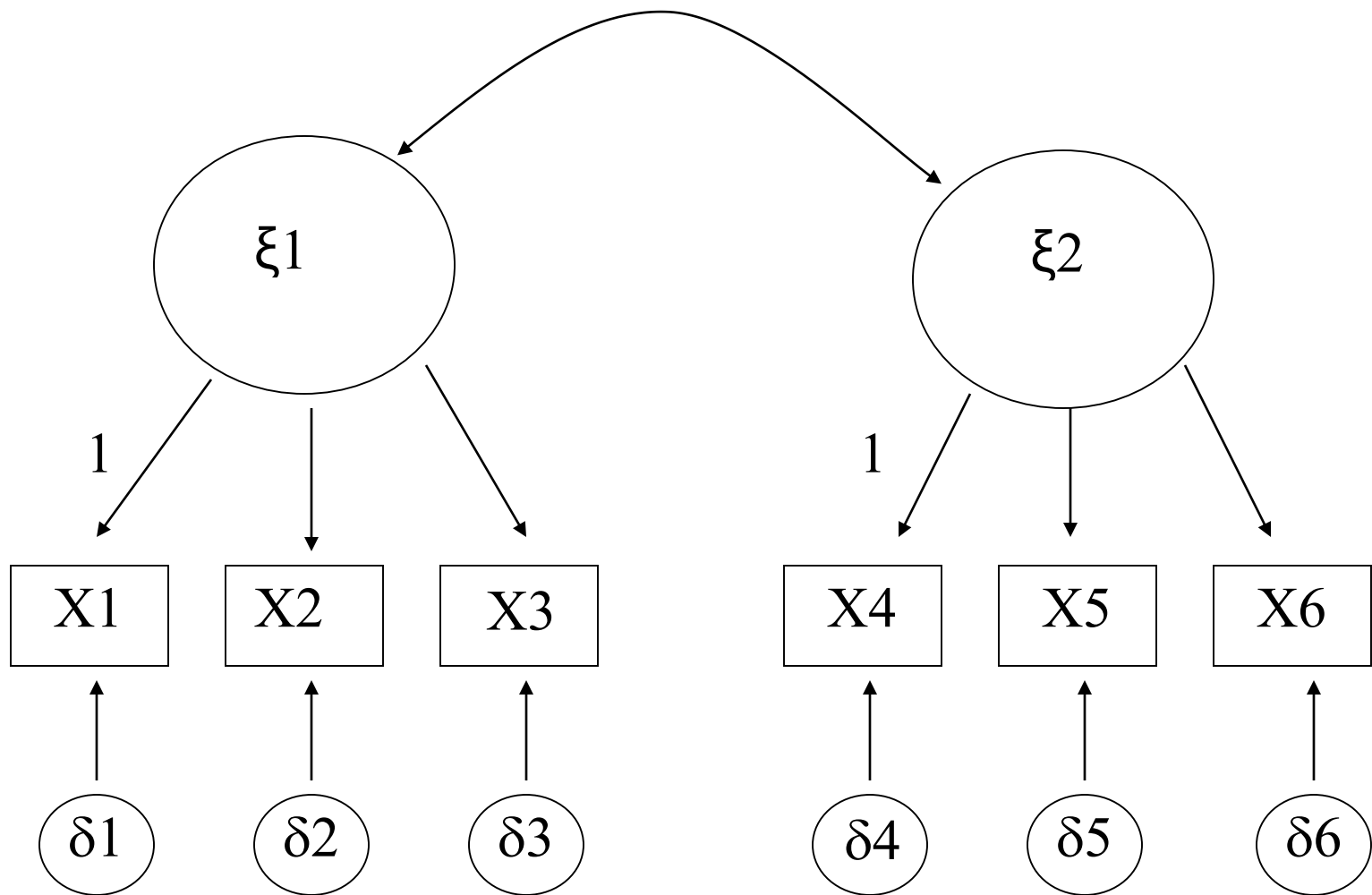
# CFA

- The null hypothesis for specific parameters
  - The parameter = 0
  - $H_0 : \lambda_{11} = 0$
  - Where  $\lambda_{11}$  is the factor loading relating Factor 1 to Variable 1
  - Evaluated with a z-test
  - In short, significance is “good”

# CFA



# CFA





# CFA

$$\mathbf{x} = \Lambda_{\mathbf{x}} \boldsymbol{\xi} + \boldsymbol{\delta}$$
$$\begin{pmatrix} \mathbf{x1} \\ \mathbf{x2} \\ \mathbf{x3} \\ \mathbf{x4} \\ \mathbf{x5} \\ \mathbf{x6} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ 0 & 1 \\ 0 & \lambda_{52} \\ 0 & \lambda_{62} \end{pmatrix} \begin{pmatrix} \boldsymbol{\xi}_1 \\ \boldsymbol{\xi}_2 \end{pmatrix} + \begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \end{pmatrix}$$

# CFA

$$\begin{aligned}\Sigma(\Theta) &= E(\mathbf{x}\mathbf{x}') = [(\Lambda_x \xi + \delta) (\xi' \Lambda_x' + \delta')] \\ &= \Lambda_x \phi \Lambda_x' + \Theta_\delta\end{aligned}$$

$\Theta_\delta$  = covariance matrix of  $\delta$

$\phi$  = covariance matrix of  $\xi$

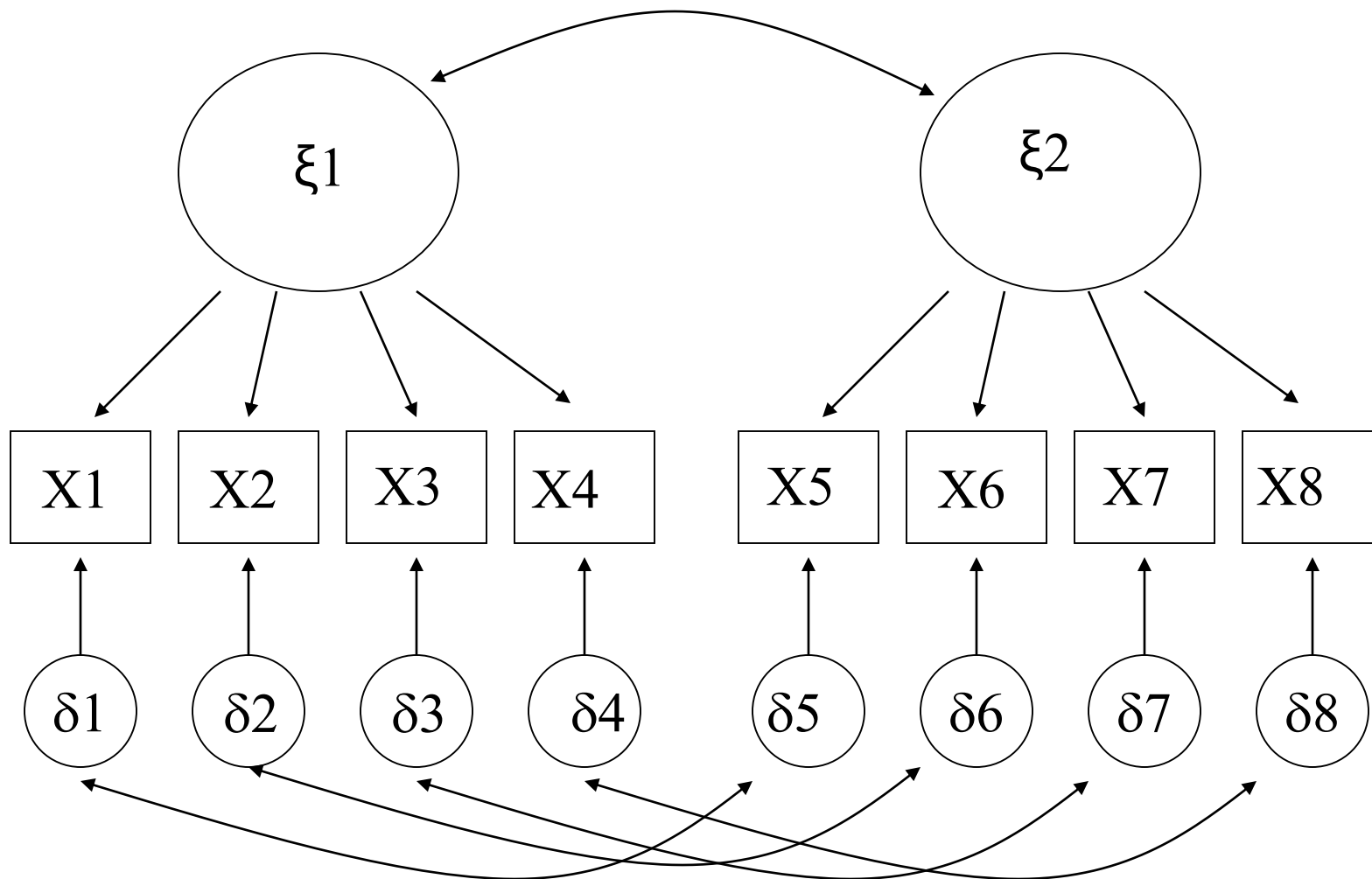
$\Lambda_x$  consists of 4 parameters (4 weights)

$\phi$  consists of 3 parameters (2 variances, 1 covariance)

$\Theta_\delta$  consists of 12 parameters (6 variances, 0 covariances)

$$df = 21 - 13 = 8$$

# CFA



# CFA

$$\mathbf{x} = \Lambda_{\mathbf{x}} \boldsymbol{\xi} + \boldsymbol{\delta}$$

$$\begin{pmatrix} \mathbf{x1} \\ \mathbf{x2} \\ \mathbf{x3} \\ \mathbf{x4} \\ \mathbf{x5} \\ \mathbf{x6} \\ \mathbf{x7} \\ \mathbf{x8} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ \lambda_{41} & 0 \\ 0 & 1 \\ 0 & \lambda_{62} \\ 0 & \lambda_{72} \\ 0 & \lambda_{82} \end{pmatrix} \begin{pmatrix} \boldsymbol{\xi}_1 \\ \boldsymbol{\xi}_2 \end{pmatrix} + \begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \\ \delta_7 \\ \delta_8 \end{pmatrix}$$

# CFA

$$\begin{aligned}\Sigma(\Theta) &= E(\mathbf{x}\mathbf{x}') = [(\Lambda_x \xi + \delta) (\xi' \Lambda_x' + \delta')] \\ &= \Lambda_x \phi \Lambda_x' + \Theta_\delta\end{aligned}$$

$\Theta_\delta$  = covariance matrix of  $\delta$

$\phi$  = covariance matrix of  $\xi$

$\Lambda_x$  consists of 6 parameters (6 weights)

$\phi$  consists of 3 parameters (2 variances, 1 covariance)

$\Theta_\delta$  consists of 12 parameters (8 variances, 4 covariances)

$$df = 36 - 21 = 15$$

# CFA Model Fit

- Model fit
  - Types of fit indices
    - Absolute fit indices
    - Incremental fit indices
    - Parsimony-adjusted indices
  - Chi-square/df ratio
    - See Kline p. 272
  - For more on the math of model fit:
    - <http://www.davidakenny.net/cm/fit.htm>

# CFA Model Fit

- Model fit
  - Kline recommends:
    - Chi-square, df, p
    - SRMR (absolute)
    - CFI (incremental)
    - RMSEA (other)

# Fit indices

- Fit indices consider the fit of the model relative to the
  - Saturated model
    - Perfectly reproduces the sample covariance matrix because all relations are specified ( $df = 0$ )
  - Independence model
    - Predicts no relations among variables



# Absolute fit indices

- Evaluate the fit of the model relative to the saturated model
  - GFI
    - $\text{GFI and AGFI} = 1$  for the saturated model
  - AGFI
    - $\text{GFI and AGFI} = 1$  for the saturated model
  - SRMR (standardized root mean square residual)
    - $\text{SRMR} = 0$  for the saturated model
    - The larger the value the worse the fit

# Incremental (comparative) fit indices

- Evaluate the fit of the model relative to a simpler baseline model, typically the independence model
  - NFI
  - TLI
  - CFI

# Other measures

- RMSEA
  - No penalty for model complexity
- AIC
  - Akaike Information Criterion
  - Intended for model comparisons
  - Considers fit and complexity

# What is “good” model fit?

- Chi-square  
 $p \geq .05$   
 $(\chi^2 / df) \leq 3.00$
- Absolute fit indices  
GFI, AGFI  $\geq .95$   
SRMR  $\leq .08$
- Incremental fit indices  
CFI, TLI  $\geq .95$
- Other measures  
RMSEA  $\leq .06$  to  $.08$

# What is “good” model fit?

- Hu, L., & Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model. A Multidiscip. J.* **1999**, 6, 1–55.
- Schreiber, J.B., Nora, A., Stage, F.K., Barlow, E.A., & King, J. Reporting structural equation modeling and confirmatory factor analysis results: A review. *J. Educ. Res.* **2006**, 99, 323–338

# Model modification

- If a path is non-significant then drop and re-run (aka Wald test)
- If a path is suggested (by modification indices) then add and re-run (aka Lagrange test)

# Model comparison

- Model A: more constrained (more parsimonious)
- Model B: less constrained (more complex)

- $\Delta\chi^2 = \chi^2_a - \chi^2_b$

- $df = df_a - df_b$

- If  $\Delta\chi^2$  is significant then choose Model B

- If  $\Delta\chi^2$  is NOT significant then choose Model A