Comparing means in a CFA framework

Recap…

• So far, you’ve run CFA within a single group
  – One input matrix

• What about cases with multiple groups?
  – Your sample may contain several groups of interest
  – Gender, race, treatment condition

• By modifying your input, you can use Mplus to test whether groups differ on the mean of the latent variable

• Advantage of CFA – modelling flexibility with latent variable
We’ll cover:

1. Multiple groups CFA
   - Model CFA in 2 or more groups simultaneously

2. Importance of measurement invariance
   - Need to be sure items function similarly in subgroups of the sample

3. MIMIC modelling
   - Alternative to multiple groups: model CFA in whole sample, and include a covariate representing group membership

Multiple groups CFA

- One major advantage of CFA over EFA is the ability to examine a model in multiple groups simultaneously

- Obvious application is the comparison of group means on a latent variable, adjusted for measurement error and an error theory

- Also enables investigation of measurement of the construct in different groups
  - Are there group differences that preclude responding in comparable ways?
  - Are some items biased against a subgroup, i.e. yield higher or lower observed scores in that group at equivalent levels of the ‘true’ score?
How?

• CFA in a single group uses a single input matrix

• CFA in multiple groups uses multiple input matrices
  – E.g. if the analysis involves 2 groups (males, females), two separate input matrices are analysed, one for each group

**Grouping syntax**

```plaintext
VARIABLE:
  NAMES ARE sex p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
USEVAR ARE p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
GROUPING IS sex (0=male 1=female);
MODEL: pos BY p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
```

---

**Single group input**

```plaintext
TITLE:
DATA:
  FILE IS risc.dat;
VARIABLE:
  NAMES ARE sex age
  p1 n2 n3 p4 n5 p6 n7 p8
  n9 n10 n11 p12 p13 p14 n15 n16
  p17 p18 n19 n20 n21 p22 p23 n24
  p25 p26 tot;
USEVARIABLES ARE
  n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
MODEL:
  risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
OUTPUT:
  SAMPSTAT MODINDICES STANDARDIZED RESIDUAL;
```
Single group output

SUMMARY OF ANALYSIS

Number of groups 1
Number of observations 359
Number of dependent variables 13
Number of independent variables 0
Number of continuous latent variables 1

Observed dependent variables

Continuous
N2  N3  N5  N7  N9  N10  N11  N15  N16  N19  N20  N21  N24

Continuous latent variables
RISC

Cont’d

TESTS OF MODEL FIT

Chi-Square Test of Model Fit
Value 192.364
Degrees of Freedom 65
P-Value 0.0000

CFI/TLI
CFI 0.772
TLI 0.726

RMSEA (Root Mean Square Error Of Approximation)
Estimate 0.074

SRMR (Standardized Root Mean Square Residual)
Value 0.066
**Cont’d**

MODEL RESULTS

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>S.E.</th>
<th>Est./S.E.</th>
<th>P-Value</th>
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<tr>
<td>RISC</td>
<td>BY</td>
<td></td>
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</tr>
<tr>
<td>N2</td>
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<td>1.000</td>
<td>0.000</td>
<td>999.000</td>
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<td>0.252</td>
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<tr>
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<td>1.622</td>
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<td>4.388</td>
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<tr>
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</tr>
<tr>
<td></td>
<td><strong>Intercepts</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>N2</td>
<td></td>
<td>1.471</td>
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<td>0.064</td>
<td>0.026</td>
<td>2.487</td>
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</table>

---

**Multiple groups input**

**TITLE:**

**DATA:**

FILE IS risc.dat;

**VARIABLE:**

NAMES ARE sex age
p1 n2 n3 p4 n5 p6 n7 p8
n9 n10 n11 p12 p13 p14 n15 n16
p17 p18 n19 n20 p21 p22 p23 n24
p25 p26 tot;

USEVARIABLES ARE
n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;

GROUPING IS sex (0= male 1= female);

**MODEL:**

risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;

**OUTPUT:**

SAMPSTAT MODINDICES STANDARDIZED RESIDUAL;
Multiple groups output

SUMMARY OF ANALYSIS
Number of groups 2
Number of observations
  Group MALE 167
  Group FEMALE 192
Number of dependent variables 13
Number of independent variables 0
Number of continuous latent variables 1

Observed dependent variables
Continuous
N2 N3 N5 N7 N9 N10 N11 N15 N16 N19 N20 N21 N24

Continuous latent variables
RISC

Variables with special functions
Grouping variable SEX

Cont’d

TESTS OF MODEL FIT

Chi-Square Test of Model Fit
  Value 319.938
  Degrees of Freedom 154
  P-Value 0.0000

CFI/TLI
  CFI 0.693
  TLI 0.689

RMSEA (Root Mean Square Error Of Approximation)
  Estimate 0.077

SRMR (Standardized Root Mean Square Residual)
  Value 0.091
Cont’d

Group MALE

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<tr>
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<th></th>
<th></th>
<th></th>
</tr>
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<td>999.000</td>
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</tr>
<tr>
<td>N3</td>
<td>0.211</td>
<td>0.203</td>
<td>1.039</td>
<td>0.299</td>
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</tr>
<tr>
<td>N5</td>
<td>1.639</td>
<td>0.375</td>
<td>4.373</td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Means</td>
<td>RISC</td>
<td>0.000</td>
<td>0.000</td>
<td>999.000</td>
<td>999.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
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<td>N3</td>
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<td>0.048</td>
<td>25.082</td>
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<tr>
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<td>N5</td>
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Group FEMALE

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<tr>
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<td>4.373</td>
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<td>Means</td>
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<tr>
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<td>0.052</td>
<td>26.834</td>
<td>0.000</td>
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<tr>
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<td>1.211</td>
<td>0.048</td>
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<tr>
<td></td>
<td>N5</td>
<td>0.716</td>
<td>0.054</td>
<td>13.193</td>
<td>0.000</td>
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<td></td>
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<tr>
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<td>0.020</td>
<td>2.388</td>
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</tbody>
</table>
What is measurement invariance?

- Measurement non-invariance occurs when people from different groups with the same underlying ability have a different probability of endorsing an item.

- Group differences on items or latent variables do not necessarily reflect measurement non-invariance.
  - E.g. girls may be higher than boys on an item or scale.

- Measurement non-invariance occurs when those differences are still present when the level of the latent variable is held constant across groups.

Invariance & bias

- Measurement invariance: the probability of item response is THE SAME among different subgroups with the same underlying ability.
  - An item is unbiased if the probability of item response depends only on the value of the latent variable.

- Measurement noninvariance: the probability of item response is DIFFERENT among different subgroups with the same underlying ability.
  - An item is biased if the probability of item response depends on the value of the latent variable, and on group membership.
Analysing measurement invariance

- Mplus enables us to test the equivalence of measurement and structural parameters of the model across multiple groups.

- Rarely addressed in applied research: measurement invariance is implicitly assumed and not examined.

- When measurement is not invariant across groups, it is misleading to analyse and interpret mean differences as ‘genuine’ differences.
  - Instead, may be due to differences in construct measurement in different groups.

Why test measurement invariance?

- Equivalence of measurement characteristics of indicators over time is necessary (but not sufficient) to demonstrate ‘true’ change.
  - E.g. Each decade, IQ scores increase (Flynn effect) but scores are not comparable over time.
  - Wicherts et al. (2004)

- It is also important to evaluate equivalence of measurement characteristics of indicators across groups.
  - E.g. IQ scores sometimes differ according to ethnicity, but scores are not necessarily comparable between groups.
  - Dolan et al. (2004)
How do we do it?

- Constrain parameters of the CFA to be equal in all groups

- Parameters may be:
  - Free: unknown, analysis finds optimal value to minimise differences between observed and predicted matrices
  - Fixed: specified by researcher to particular value (usually 0 or 1)
  - Constrained: unknown, but not free to be any value because specification places restrictions on the value it may assume

- E.g. if factor loadings are constrained to equality, the analysis finds a single estimate for all loadings

- Models are nested, so can use $\chi^2$ difference tests

Consists of...

- 1) Equal form
  - Same factor structure present in both groups

- 2) Equal loadings
  - Unit increase in latent variable is associated with comparable increase in indicator in both groups

- 3) Equal indicator intercepts
  - At a given level of the latent variable, indicators have a comparable value in both groups

- 4) Equal error variances?
  - Highly stringent, rarely holds in realistic data sets
  - Not as important as prior steps
In Mplus...

- Mplus holds the form, loadings and intercepts to equality by default

- Testing measurement invariance requires overriding these defaults

```
VARIABLE:
  NAMES ARE sex p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
  USEVAR ARE p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
  GROUPING IS sex (0=male 1=female);
ANALYSIS:
  MODEL=NOMEAN;
  INFORMATION=EXPECTED;
MODEL:
  pos BY p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
MODEL female:
```

Partial measurement invariance

- If full measurement invariance is untenable (significant increase in $\chi^2$), partial measurement invariance still possible

- Fit diagnostics (e.g. modification indices) can assist in identifying the parameters that are noninvariant
  - Relax the constraints on noninvariant parameters

```
VARIABLE:
  NAMES ARE sex p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
  USEVAR ARE p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
  GROUPING IS sex (0 = male 1 = female);
MODEL:
  pos BY p1 p4 p6 p8 p12 p13
  p14 p17 p18 p22 p23 p25 p26;
MODEL female:
p6;
```

- Free p6 intercept
- Free p12 loading
Cont’d…

• One indicator (besides marker indicator) is invariant, partial invariance supported and analysis can proceed

• Advantages:
  – Allows analysis of measurement invariance to proceed (don’t have to abandon analyses)
  – Can evaluate structural parameters (e.g. mean differences) of model in context of partial measurement invariance

• Disadvantages:
  – If many indicators are noninvariant, should question whether it is suitable to proceed with further invariance testing
  – May be more problematic when the research interest is psychometric (e.g. test development)

Equal form input

TITLE: 
DATA: 
  FILE IS risc.dat;
VARIABLE: 
  NAMES ARE sex age 
  n2 n3 n4 n5 n6 n7 p8 
  n9 n10 n11 p12 p13 p14 n15 n16 
  p17 p18 n19 n20 p22 p23 n24 
  p25 p26 tot; 
USEVARIABLES ARE 
  n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24; 
GROUPING IS sex (0=male 1=female); 
ANALYSIS: 
  MODEL=NOMEAN; 
  INFORMATION=EXPECTED; 
MODEL: 
  risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24; 
MODEL FEMALE: 
  risc BY n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24; 
OUTPUT: 
  SAMPSTAT MODINDICES STANDARDIZED RESIDUAL;
Equal loadings input

TITLE:
DATA:
   FILE IS risc.dat;
VARIABLE:
   NAMES ARE sex age
   p1 n2 n3 p4 n5 p6 n7 p8
   n9 n10 n11 p12 p13 p14 n15 n16
   p17 p18 n19 n20 n21 p22 p23 n24
   p25 p26 tot;
USEVARIABLES ARE
   n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
GROUPING IS sex (0=male 1=female);
ANALYSIS:
   MODEL=NOMEAN;
   INFORMATION=EXPECTED;
MODEL:
   risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
OUTPUT:
   SAMPSTAT MODINDICES STANDARDIZED RESIDUAL;

Chi-square difference test

Equal form
Chi-Square Test of Model Fit

<table>
<thead>
<tr>
<th>Value</th>
<th>270.656</th>
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</thead>
<tbody>
<tr>
<td>Degrees of Freedom</td>
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</tr>
<tr>
<td>P-Value</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

χ² difference = 19.025
df difference = 12
Critical value = 21.026
No significant decrease in fit = loadings are equal

Equal loadings
Chi-Square Test of Model Fit

<table>
<thead>
<tr>
<th>Value</th>
<th>289.681</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degrees of Freedom</td>
<td>142</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
Equal intercepts input

TITLE:
DATA:
   FILE IS risc.dat;
VARIABLE:
   NAMES ARE sex age
   p1 n2 n3 p4 n5 p6 n7 p8
   n9 n10 n11 p12 p13 p14 n15 n16
   p17 p18 n19 n20 n21 p22 p23 n24
   p25 p26 tot;
USEVARIABLES ARE
   n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
GROUPING IS sex (0=male 1=female);
MODEL:
   risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
OUTPUT:
   SAMPSTAT MODINDICES(5) STANDARDIZED RESIDUAL;

Chi-square difference test

Equal loadings
Chi-Square Test of Model Fit

<table>
<thead>
<tr>
<th>Value</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Degrees of Freedom</td>
<td>142</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| χ2 difference = 30.257 |
| df difference = 12    |
| Critical value = 21.026 |
| Significant decrease in fit = intercepts NOT equal |

Equal intercepts
Chi-Square Test of Model Fit

<table>
<thead>
<tr>
<th>Value</th>
<th>319.938</th>
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</thead>
<tbody>
<tr>
<td>Degrees of Freedom</td>
<td>154</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| χ2 difference = 30.257 |
| df difference = 12    |
| Critical value = 21.026 |
| Significant decrease in fit = intercepts NOT equal |
Modification indices

Means/Intercepts/Thresholds

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>N19</td>
<td>6.828</td>
<td>0.144</td>
<td>0.144</td>
<td>0.171</td>
</tr>
<tr>
<td>N20</td>
<td>5.425</td>
<td>-0.126</td>
<td>-0.126</td>
<td>-0.141</td>
</tr>
<tr>
<td>N24</td>
<td>5.783</td>
<td>-0.119</td>
<td>-0.119</td>
<td>-0.142</td>
</tr>
</tbody>
</table>

Suggests that the intercepts of these three indicators are not invariant, and should be freed

Partial intercepts input

```
TITLE:
DATA:
  FILE IS risc.dat;
VARIABLE:
  NAMES ARE sex age
  p1 n2 n3 p4 n5 p6 n7 p8
  n9 n10 n11 p12 p13 p14 n15 n16
  p17 p18 n19 n20 n21 p22 p23 n24
  p25 p26 tot;
USEVARIABLES ARE
  n2 n3 n5 n7 n9 n10 n11 n16 n19 n20 n21 n24;
GROUPING IS sex (0=male 1=female);
MODEL:
  risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
MODEL FEMALE:
  [n19];
  [n24];
  [n20];
OUTPUT:
  SAMPSTAT MODINDICES(5) STANDARDIZED RESIDUAL;
```
Chi-square difference test

Equal loadings
Chi-Square Test of Model Fit

<table>
<thead>
<tr>
<th>Value</th>
<th>289.681</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degrees of Freedom</td>
<td>142</td>
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<tr>
<td>P-Value</td>
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</table>

Partial intercepts
Chi-Square Test of Model Fit

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<th>Value</th>
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<td>Degrees of Freedom</td>
<td>151</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

χ² difference = 13.257
df difference = 9
Critical value = 16.919
No significant decrease in fit = remaining intercepts are equal

Then test population homogeneity…

- Having established equivalence of measurement parameters, then assess equivalence of structural parameters
  - Comparison of group means only meaningful when measurement properties are invariant

- Equal variances
  - The groups drew from similar ranges of the latent variable to respond to its indicators
  - Often does not have substantive implications in applied research, but is a necessary step before comparing means

- Equal means
  - Groups do not differ in their levels of the latent variable
In Mplus…

- Mplus does NOT hold structural parameters (factor variances, factor means) to equality by default

- Need to add these constraints

```plaintext
VARIABLE:
NAMES ARE sex p1 p4 p6 p8 p12 p13
p14 p17 p18 p22 p23 p25 p26;
USEVAR ARE p1 p4 p6 p8 p12 p13
p14 p17 p18 p22 p23 p25 p26;
GROUPING IS sex (0 = male 1 = female);
MODEL: pos BY p1 p4 p6 p8 p12 p13
p14 p17 p18 p22 p23 p25 p26;
pos(1);
MODEL MALE: pos@0;
```

Interpreting mean differences

- One group’s mean is fixed to zero; this becomes the reference group

- Mean in the other group(s) is freely estimated, but this parameter represents the deviation from the reference group’s mean
  - Because indicator intercepts have been held to equality across groups, the latent factors have an arbitrary mean
  - Latent means are not estimated in the absolute sense, but reflect differences in the mean level of the latent variable across groups
Population homogeneity input

DATA:
  FILE IS risc.dat;
VARIABLE:
  NAMES ARE sex age
  p1 n2 n3 p4 n5 p6 n7 p8
  n9 n10 n11 p12 p13 p14 n15 n16
  p17 p18 n19 n20 n21 p22 p23 n24
  p25 p26 tot;
USEVARIABLES ARE
  n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
GROUPING IS sex (0=male 1=female);
MODEL:
  risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
  risc(1);
MODEL FEMALE:
  [n19];
  [n24];
  [n20];
OUTPUT:
  SAMPSTAT MODINDICES(5) STANDARDIZED RESIDUAL;

Population homogeneity output

Group MALE

Means
  RISC    0.000    0.000  999.000  999.000
Variances
  RISC    0.058    0.024    2.470    0.014

Group FEMALE

Means
  RISC    0.149    0.042    3.583    0.000
Variances
  RISC    0.058    0.024    2.470    0.014

On average, females score .15 units higher than males on the RISC, based on the metric of the marker indicator.
> 2 groups

- Can use multiple-groups CFA to examine mean differences in more than 2 groups

- Change which group’s mean is fixed to zero, and examine the individual parameters

---

**Change reference group**

VARIABLE:
- NAMES ARE sex age
  p1 n2 n3 p4 n5 p6 n7 p8
  n9 n10 n11 p12 p13 p14 n15 n16
  p17 p18 n19 n20 n21 p22 p23 n24
  p25 p26 tot;
- USEVARIABLES ARE
  n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
- GROUPING IS sex (0=male 1=female);

MODEL:
- risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
  risc(1);

MODEL MALE:
  [risc*];

MODEL FEMALE:
  [n19];
  [n24];
  [n20];
  [risc@0];

OUTPUT:
- SAMPSTAT MODINDICES(5) STANDARDIZED RESIDUAL;
Output

Group MALE

Means
RISC       -0.149  0.042  -3.583  0.000
Variances
RISC       0.058  0.024   2.470  0.014

Group FEMALE

Means
RISC       0.000  0.000  999.000  999.000
Variances
RISC       0.058  0.024   2.470  0.014

MIMIC

- Multiple indicators, multiple causes

- Regress latent variables onto covariates that represent group membership
  - E.g. sex: 0 = male, 1 = female

- Uses a single input matrix: allows for examination of group differences in a smaller sample

- Significant effect of covariate on latent factor represents population heterogeneity; significant effect on indicator represents differential item functioning
In Mplus…

- Regress latent variable onto group covariate

- Hold regression of indicators onto group covariate to zero (assume no direct effect of group membership on indicator)

VARIABLE:
pos ON sex;
p1 p4 p6 p8 p12 p13 p14 p17 p18 p22 p23 p25 p26 ON sex@0;

MIMIC input

TITLE:
DATA:
FILE IS risc.dat;
VARIABLE:
NAMES ARE sex age p1 n2 n3 p4 n5 p6 n7 p8 n9 n10 n11 p12 p13 n14 n15 n16 n17 p18 n19 n20 n21 p22 p23 n24 p25 p26 tot;
USEVARIABLES ARE sex n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
MODEL:
risc BY n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24;
risc ON sex;
n2 n3 n5 n7 n9 n10 n11 n15 n16 n19 n20 n21 n24 ON sex@0;
OUTPUT:
SAMPSTAT MODINDICES STANDARDIZED RESIDUAL;
MODEL RESULTS

<table>
<thead>
<tr>
<th>Estimate</th>
<th>S.E.</th>
<th>Est./S.E.</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RISC ON</td>
<td>0.158</td>
<td>0.042</td>
<td>3.750</td>
</tr>
</tbody>
</table>

Gender coded: 0=male, 1=female

On average, females score .16 units higher than males on the RISC, based on the metric of the marker indicator.

If gender was coded 0=female, 1=male, this parameter would be the same but negative.

Multiple groups vs. MIMIC

- Multiple groups requires a larger sample than single group CFA with MIMIC
  - Sample must be large enough to be subdivided into 2 or more groups, so that each input matrix can be analysed separately

- MIMIC modelling only tests two potential sources of invariance in the model
  - Regressing the covariate onto the indicators tests for the equivalence of indicator intercepts in both groups
  - Regressing the covariate onto the latent variable tests for the equivalence of factor means across groups
  - Multiple groups CFA tests all aspects of measurement invariance (form, loadings, intercepts) and population homogeneity (variances, means)