2.1.2 British Household Panel example. Correlated residuals

Example: British Household Panel Data (N = 589) EFA with Correlated Residuals

Wording and Hypothesized Factor Loading Pattern for the 15 Items Used to Measure the Big Five Personality Factors in the British Household Panel Data ("I See Myself As Someone Who...")

Item	A	C	E	N	O
y1: Is sometimes rude to others (reverse scored)	X	0	0	0	0
y2: Has a forgiving nature	X	0	0	0	0
y3: Is considerate and kind to almost everyone	X	0	0	0	0
y4: Does a thorough job	0	X	0	0	0
y5: Tends to be lazy (reverse scored)	0	X	0	0	0
y6: Does things efficiently	0	X	0	0	0
y7: Is talkative	0	0	X	0	0
y8: Is outgoing, sociable	0	0	X	0	0
y9: Is reserved (reverse scored)	0	0	X	0	0
y10: Worries a lot	0	0	0	X	0
y11: Gets nervous easily	0	0	0	X	0
y12: Is relaxed, handles stress well (reverse scored)	0	0	0	X	0
y13: Is original, comes up with new ideas	0	0	0	0	X
y14: Values artistic, aesthetic experiences	0	0	0	0	X
y15: Has an active imagination	0	0	0	0	X

Note. A = Agreeableness; C = Conscientiousness; E = Extraversion; N = Neuroticism; O = Openness.

Slide 18 shows a different example using data from the British Household Panel. A simple loading pattern for 5 factors is hypothesized. The factor names are listed below the table. This measurement instrument has 4 indicators that have negative statements as opposed to all the other indicators so they are reverse scored.

This example illustrates EFA with correlated residuals using ESEM.

EFA and ESEM Inputs

EFA

```
ANALYSIS:
          TYPE = EFA 5 5;
```

ESEM

```
MODEL:
          f1-f5 BY y1-y15 (*1);
```

ESEM with residual covariances

```
MODEL:
          f1-f5 BY y1-y15 (*1);
          y1 y5 y9 y12 WITH y1 y5 y9 y12;
```

- 6 residual covariances for the reverse-scored items y1, y5, y9, y12 (Marsh et al., 2013)

Slide 19 shows EFA and ESEM inputs for this dataset. The bottom input shows the strength of ESEM in that it can include residual covariances in the model. These residual covariances are added for the reverse scored indicators per suggestion of the paper by Marsh et al. (2013) which analyzed this dataset. In this way, negatively worded indicators are allowed to correlate beyond what the factors would predict.

BHP 5-Factor Solutions Using MLR

Model	# par's	LL	BIC	χ^2	Df	P	CFI
1. CFA	55	-11647	23645	415	80	0	0.78
2. CFA + 6 rescovs	61	-11610	23609	348	74	0	0.82
3. EFA	95	-11446	23498	101	40	0	0.96
4. EFA + 6 rescovs	101	-11430	23504	80	34	0	0.97

- CFA models 1 and 2 are outperformed by EFA models 3 and 4 as judged by BIC
- EFA model 3 does not capture hypothesized F1 and F2 factors
- EFA + rescovs model 4 needed which can be done by ESEM (input on previous slide)

Slide 20 shows the model fit for 4 different models. Comparing the CFA models 1 and 2, it is seen that the addition of the 6 residual covariances is warranted given better BIC and CFI. The CFA models are however outperformed by the two EFA models in terms of BIC. The EFA models also have better CFI. EFA model 3 has the best BIC but it doesn't capture the first two factors. Not adding the residual covariances throws off the modeling. EFA model 4 which is done by ESEM gives a BIC value only slightly worse than for model 3 and is the model of choice.