

KATHOLIEKE UNIVERSITEIT

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Explaining cross-national inequivalence A Bayesian Multilevel SEM approach

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Introduction



- Challenges in measurement equivalence testing
 - Large-scale surveys: increasing number of contexts
 - What to do if equivalence cannot be established?
- Outline:
 - MLSEM approach to measurement equivalence
 - The two-level CFA model
 - Measurement equivalence
 - Bayesian estimation
 - Illustration: citizenship conceptions in ISSP
 - Explaining random slope variation
 - Simulation study

Two-level CFA model



- A multilevel approach to CFA (Muthen 1994)
 - Starting point: population of individuals *i* divided into *g* groups
 - Decomposition of individual data into within group and between group components:

$$X_{ig} = X_W + X_B$$
$$X_{ig} = (X_{ig} - \overline{X_g}) + \overline{X_g}$$

 Orthogonal decomposition of total covariance structure into within- and between-group covariance structures:

$$\Sigma_T = \Sigma_W + \Sigma_B$$

Two-level CFA model

 One model that simultaneously predicts within- and between-group components of the data:

$$X_{ig} = \alpha_g + \Lambda_W \eta_W + \delta_{Wig} \quad (1)$$

$$\alpha_g = \nu + \Lambda_B \eta_B + \delta_{Bg} \quad (2)$$

• Substition of (2) into (1)

$$\mathbf{X}_{ig} = \mathbf{v} + \Lambda_W \eta_W + \Lambda_B \eta_B + \delta_{Bg} + \delta_{Wig}$$

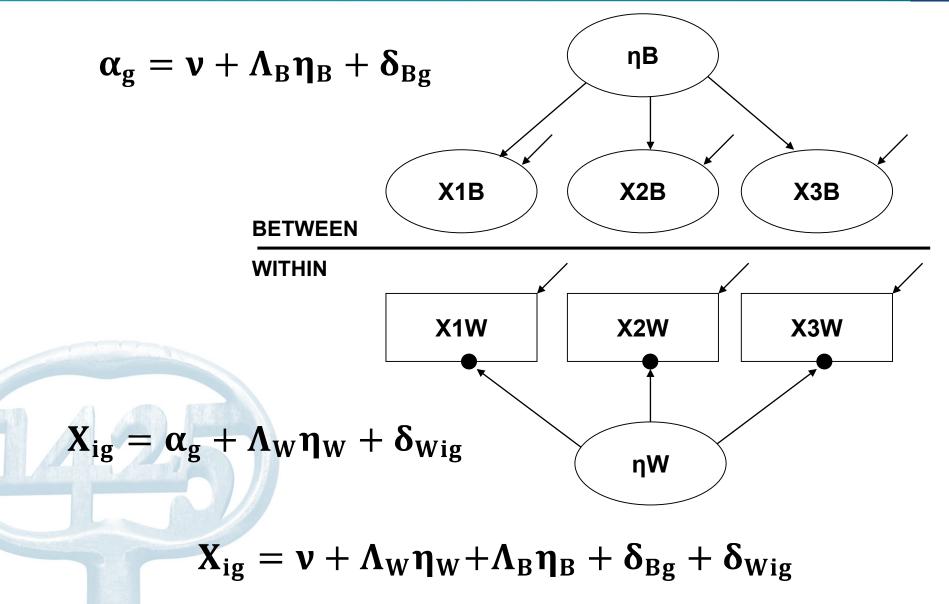
• This model implies:

$$\Sigma_{\mathrm{W}} = \Lambda_{\mathrm{W}} \Phi_{\mathrm{W}} \Lambda'_{\mathrm{W}} + \Theta_{\mathrm{W}}$$

 $\Sigma_{\mathrm{B}} = \Lambda_{\mathrm{B}} \Phi_{\mathrm{B}} \Lambda'_{\mathrm{B}} + \Theta_{\mathrm{B}}$

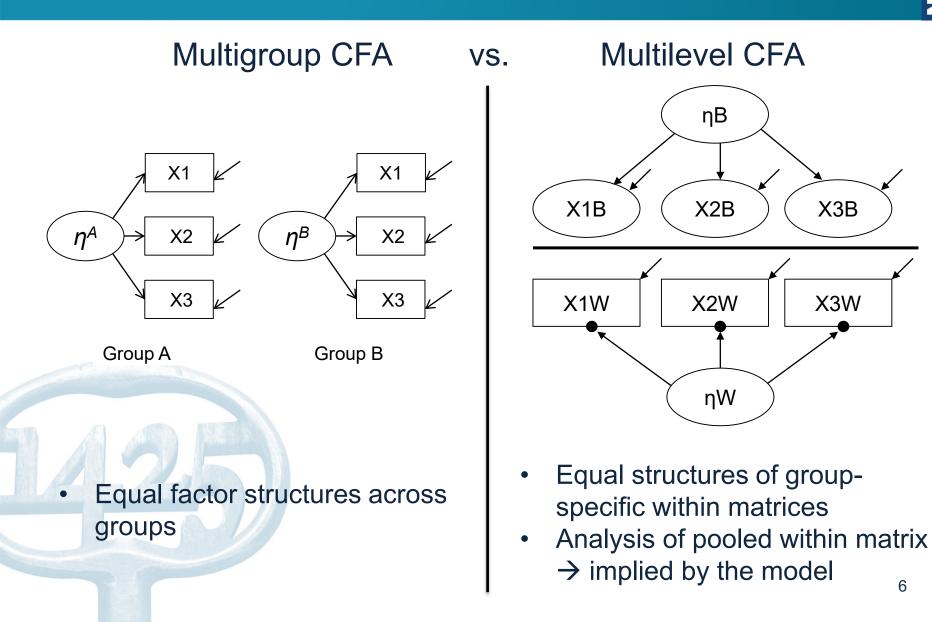
Two-level CFA model





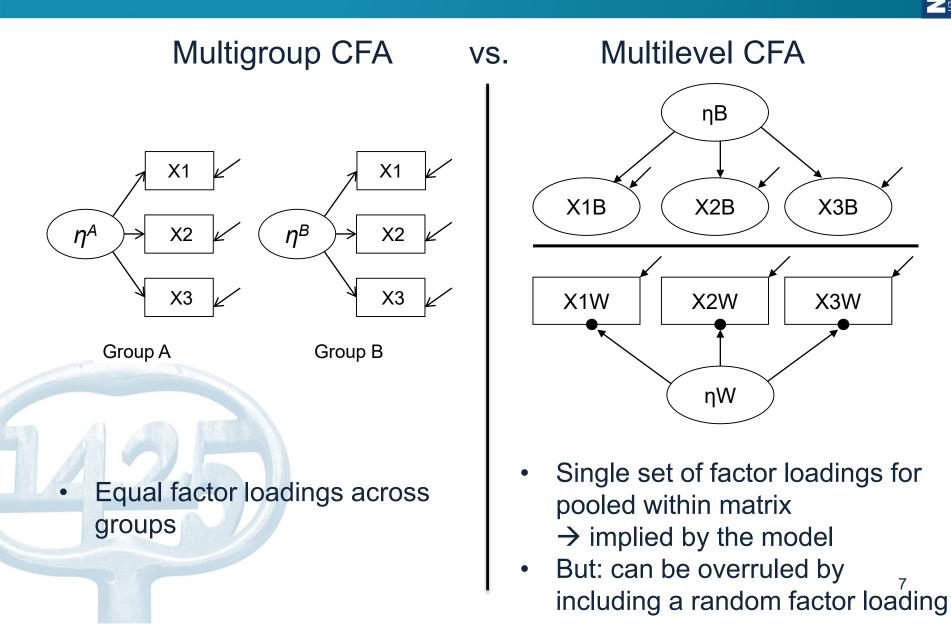
Configural equivalence





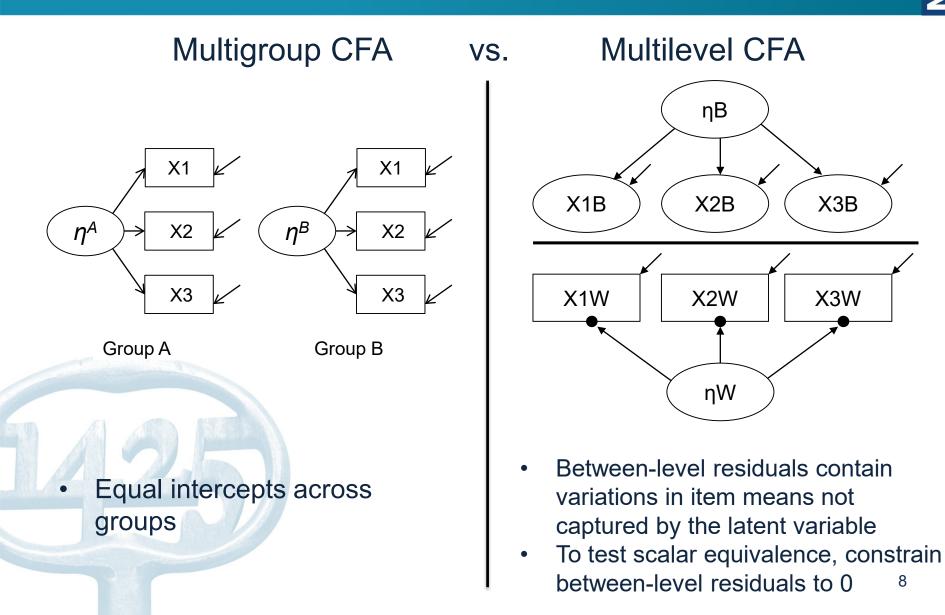
Metric equivalence



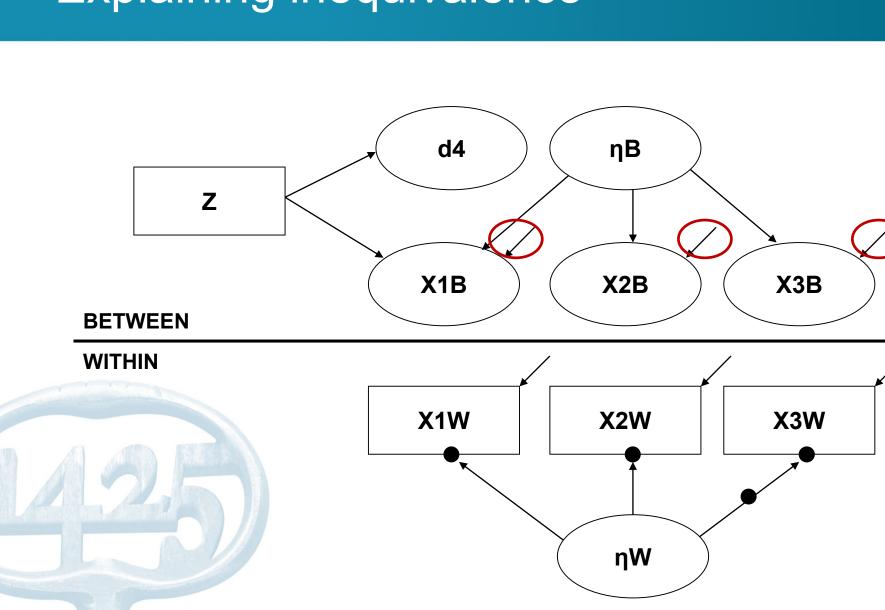


Scalar equivalence

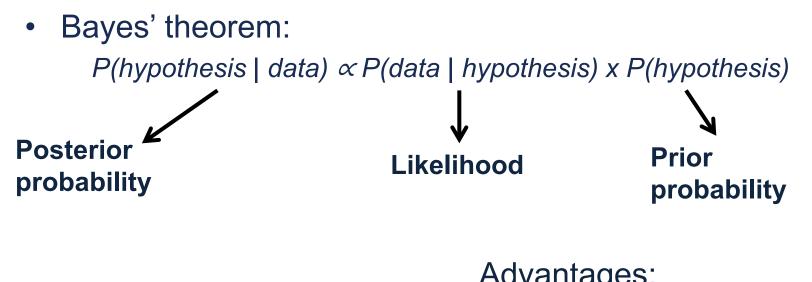


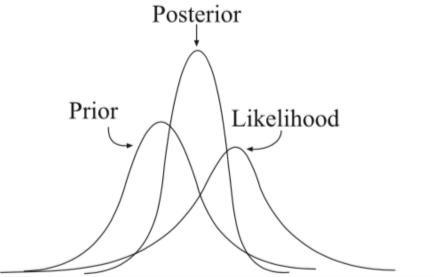


Explaining inequivalence



Bayesian estimation





Advantages:

- More can be learned from 1 parameters
- **Better small-sample** 2. performance
- Computationally less 3. demanding
- New types of models can be 4. analyzed

- Explaining slope differences in MLSEM:
 - International Social Survey Program
 - 2003 wave: focus on national identity
 - 32 societies

International Social Survey Programme 2008





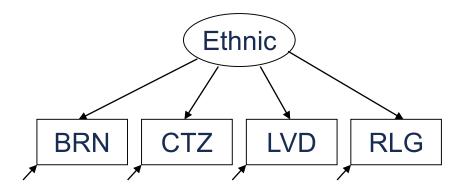
Scale measuring ethnic citizenship conceptions:

Some people say that the following things are important for being truly [NATIONALITY]. Others say they are not important. How important do you think each of the following is?

- To have been born in the country (**BRN**)
- To have [COUNTRY NATIONALITY] citizenship (CTZ)
- To have lived in [COUNTRY] for most of one's life (LVD)
- To be a [RELIGION] (RLG)
- Answer scale: very important (1) not important at all (4) (reversed) 12



• MGCFA for 32 groups:

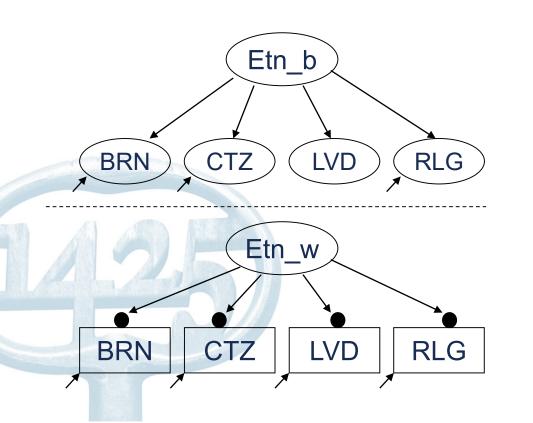


	Chi2	Df	RMSEA	CFI	TLI	SRMR
Configural equivalence	359.658	64	0.063	0.992	0.976	0.018
Metric equivalence	2440.424	157	0.112	0.939	0.926	0.145
Scalar equivalance	10850.897	250	0.191	0.718	0.783	0.244

Application: citizenship Content of Content



- Two-level CFA:
 - Bayesian estimation
 - Uninformative priors
 - 10.000 iterations

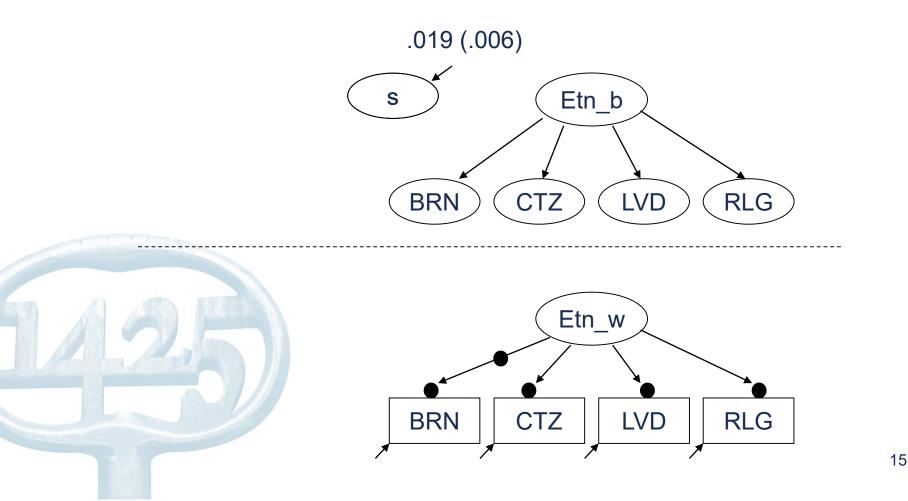


BRIN	0.787			
CTZ	0.693*			
LVD	0.689*			
RLG	0.426*			
Residual Variances				
BRN	0.381*			
CTZ	0.52*			
LVD	0.526*			
RLG	0.819*			

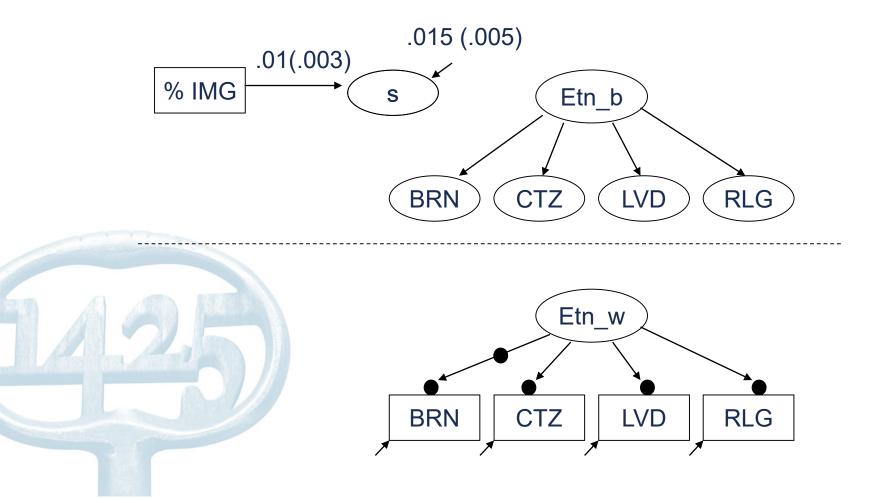
BETWEEN MODEL

Factor loadings				
BRN	0.973*			
CTZ	0.694*			
LVD	0.962*			
RLG	0.747*			
Residual Variances				
BRN	0.053*			
CTZ	0.518*			
LVD	0.075*			
	0.075			

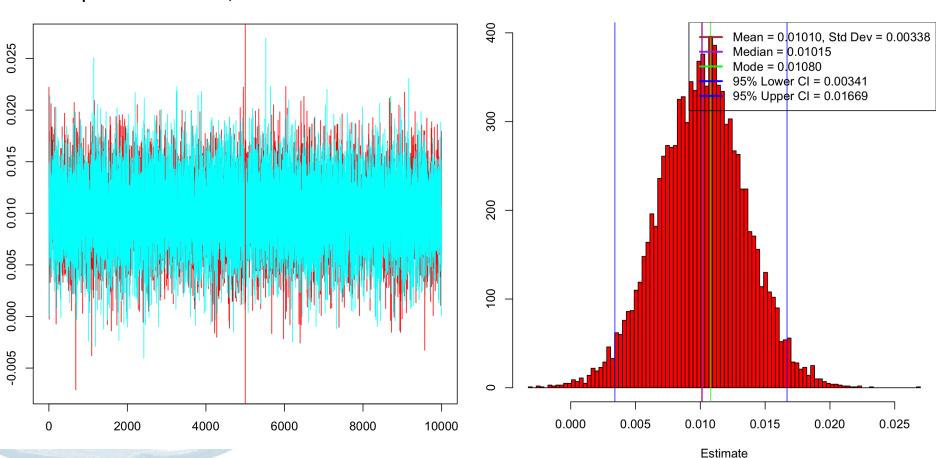
• Set factor loading for BRN random:



Effect of % of immigrants (UNDP estimate) on slope variance:







Trace plot of: Parameter 19, %BETWEEN%: S1 ON MIGPER

Distribution of: Parameter 19, %BETWEEN%: S1 ON MIGPER



• Monte Carlo simulation (500 replications)

	WITHIN			BETWEEN			
	Parameter bias	SE bias	Coverage	Parameter bias	SE bias	Coverage	
Factor loadings							
ltem1	0.03%	1.89%	0.946	6.83%	21.66%	0.952	
ltem2	-0.03%	1.89%	0.958	7.20%	12.11%	0.938	
ltem3	-0.03%	0.00%	0.95	6.50%	14.17%	0.932	
Item 4	0.08%	0.00%	0.956	6.83%	13.16%	0.938	
Residual variances							
ltem1	0.04%	2.00%	0.952	13.24%	25.00%	0.952	
Item2	-0.02%	-1.92%	0.946	11.21%	20.51%	0.952	
Item3	-0.02%	-3.77%	0.938	12.04%	18.99%	0.952	
Item4	0.04%	-5.66%	0.946	14.41%	14.29%	0.928	
Random slope				7.98%	14.89%	0.946	
Effect of Z				-0.14%	9.01%	0.950 ⁸	

Conclusion



- In some cases, measurement inequivalence can be a source of information rather than just nuisance
- MLSEM can help to explain why slopes (and intercepts) vary across groups
- It might even be possible to explain inequivalence away
- Bayesian estimation produces sufficiently reliable inference, even with small sample sizes
- Unresolved issues:
 - Model fit indices in Bayesian MLSEM?
 - Set free multiple factor loadings (cfr. IRT approach)?
 - Small-variance priors on the factor loading variances?



Thank you for your attention!

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