Multilevel Modellingcourse: DAY 2

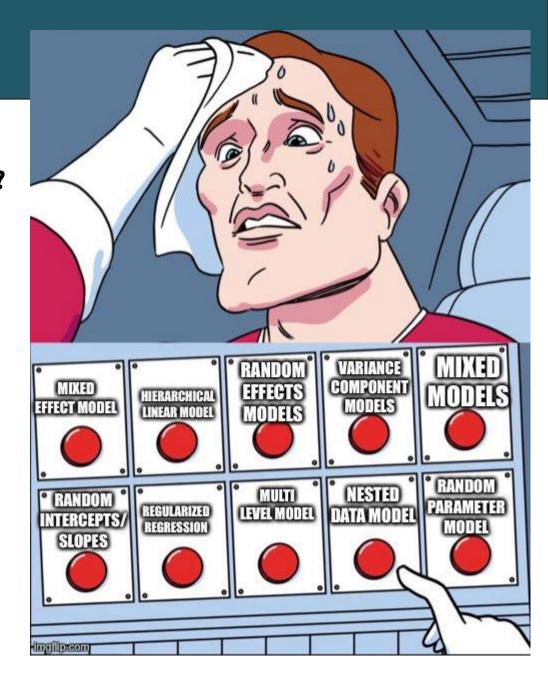
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Schedule for Day 2

- What happened so far, and where are we heading?
- Fixed Effects models
- 3-Level models (and more)
- Cross-level interactions and centering
- Mediation

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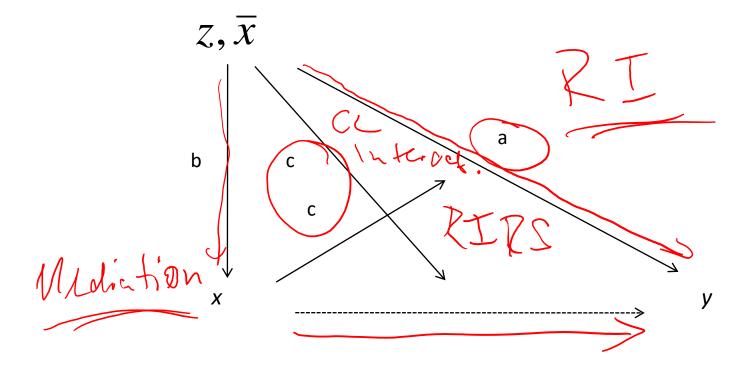


What happened so far? (1/4)

- We talked about multilevel data structures and why it is important to account for dependent observations
- With dependent observations, OLS...
 - …leads to biased SEs
- ...might lead to biased coefficient estimates
 - ...is not able to estimate individual-level *and* contextual effects

What happened so far? (3/4)

We talked about contextual effects and possible variables relationships



What happened so far? (3/4)

 We reviewed typical steps in multilevel analysis and went into their technicalities

- 1. (Empty model) |CC > 2.5 / 3%
- 2. Random Intercept Model, individual variables only
- 3. Random Intercept Model, individual variables and context variables
- 4. Random Slopes Model -> for love level var.
- 5. Random Slopes Model, with cross-level interactions

What happened so far? (4/4)

- We talked about...
 - Model estimation (Maximum Likelihood)
 - Model comparison (Likelihood-Ratio-Tests, AIC, BIC, R^2)
 - Model assumptions (linearity, normally distributed errors, homoscedasticity, and as always exogenous predictor variables)

Tried out some examples in R and Stata

How we proceed (1/2)

- Important stuff, we will focus on in the remaining time
 - Fixed effects versus random effects (aka multilevel) models
 - Interactions (very relevant!) and centering (not a big issue)
 - Practical guide to mediation (complex topic, so we cover only the basics)
 - 3- and more levels (not difficult to implement) and multilevel models with some fixed effects (very useful and underated)

How we proceed (2/2)

- Relevant stuff that, however, goes beyond a practical introduction:
 - Cross-classified models (complex and not often used)
 - Logistic multilevel regression for binary outcomes (adds some complexity, often produces substantively similar results compared to a linear model)
 - Growth curve models (useful for time-related data)

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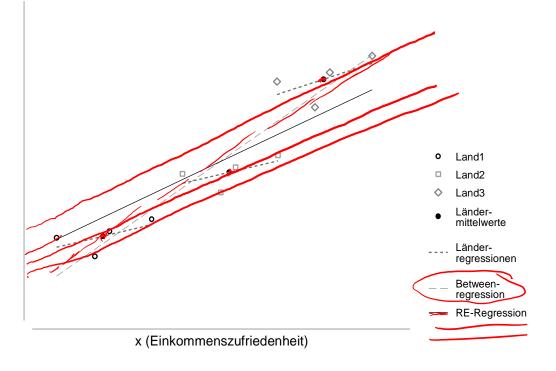
Remedies to statistical dependencies

- Control for factors that causally underlie the process of serial correlation
- Estimation of cluster / panel-robust standard errors
- Random effects a.k.a. multilevel models
- Fixed effect models

Random effects / multilevel models

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 z_j + u_j + e_{ij}$$

- Similar to OLS models: estimation based on both between-group and within-group variance, but weighted toward within estimates
- Variance between groups is bound in the error term, which is assumed to be a normally distributed random variable $u_{\it j}$
- Contextual factors (e.g. GDP/pc) can be used to explain variance between groups



Fixed effects model

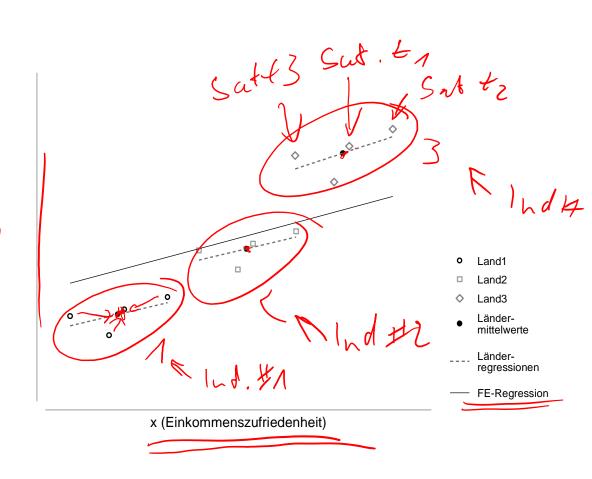
• **Basic version:** OLS regression with a dummy variable for each group j

$$y_{ij} = \beta_0 + \sum_{j=1}^{J-1} \beta_j D_{j[i]} + \beta_1 x_{ij} + e_{ij}.$$

Dummy variable: absorbs the complete variance between groups

- → predictor no longer confounded with group differences in the outcome
- Demeaning (same results): Centering the variables on the respective group average (i.e., the within estimator, as it is based on within variance only)

$$(y_{ij} - \bar{y}_j) = \beta_1(x_{ij} - \bar{x}_j) + (e_{ij} - \bar{e}_j).$$



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Fixed effects model

Pros:

- Avoids biased estimators due to unobserved group-level heterogeneity
- Adjust for serial correlation

Cons:

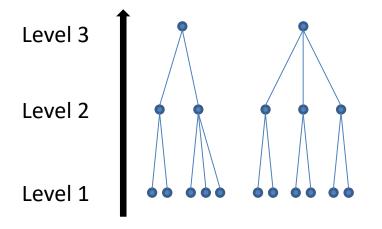
- Group-level variables cannot be included
- Low efficiency (= potentially SEs too high)

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3 – Level Model

- Individuals in regions (L-2) in countries (L-3)
- Pupils in classes (L-2) in schools (L-3)
- Workers in teams (L-2) in organisations (L-3)
- Repeated measurements in individuals (L-2) in regions (L-3)



3-Level Model

Extension of the 2-Level Model

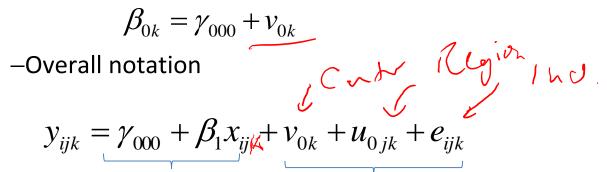
-Random Intercept Modell $y_{ijk} = \beta_{0jk} + \beta_{1jk} x_{ijk} + e_{ijk}$

–Region-in-Country-Intercept

$$\beta_{0jk} = \beta_{0k} + u_{0jk}$$

-Country-Intercept

$$\beta_{0k} = \gamma_{000} + \nu_{0k}$$



3-Level Model

Variance components (ICC)

-Level 2
$$\rho = \frac{\sigma_{u_{0jk}}^{2}}{\sigma_{e}^{2} + \sigma_{u_{0}jk}^{2} + \sigma_{v_{0k}}^{2}}$$



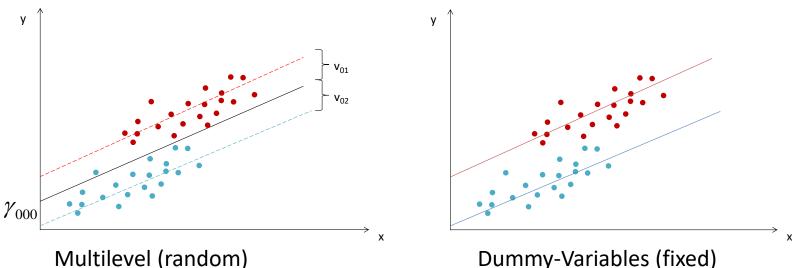
$$\rho = \frac{\sigma_{u_{0jk}}^{2} + \sigma_{v_{0k}}^{2}}{\sigma_{e}^{2} + \sigma_{u_{0}jk}^{2} + \sigma_{v_{0k}}^{2}}$$

$$\rho = \frac{\sigma_{v_{0k}}^{2}}{\sigma_{e}^{2} + \sigma_{u_{0}jk}^{2} + \sigma_{v_{0k}}^{2}}$$
-Level 3

- Complexity of the models grows exponentially with the number of levels
 - Random slopes can occur at all higher levels (individual effect at level-2 and level-3; regional effect at level-3 ...)
 - Increasing number of possible cross-level interactions

Accounting for various levels in multilevel modeling

- Levels can be account for by random intercepts (=level) or unit fixed effects
- With random intercepts, the problem of unobserved heterogeneity remains
- With fixed effects, variance is not modelled, but absorbed
 - Advantage with multiple levels: Multilevel structure at lower levels is taken into account, no distortions due to unobserved heterogeneity (useful for repeated cross-sectional survey data and an interest in time-varying macro-level predictors, e.g., changes in income inequality over time
 - Disadvantage: No macro variables can be estimated at the level of unit fixed effects



Accounting for various levels in multilevel modeling

Table 1. A typology of random effects structures for multilevel models of comparative longitudinal survey data

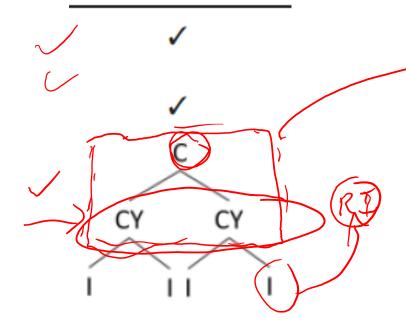
	Random effects	Model A	Model B	Model C	Model D	Model E	Model F
	Country		✓		1	✓	✓
	Year			✓		✓	✓
→	Country-year	✓		✓	✓		✓
	Structure	CY	С	Υ	С	C Y	C Y
				I CY CY	CY CY	\rightarrow	\bigwedge
				1 11 1	1 11 1	1 1	CY CY
						/	
							/1 11 1

Note: C=country-level RE, Y = year-level RE, CY = country-year-level RE, I = individual level.

Source: Schmidt-Catran & Fairbrother 2016 (Eur Soc Rev): p.25

Accounting for various levels in multilevel modeling

Model D



Plus time and country dummies

With repeated cross-sectional survey data (e.g., ESS, ISSP) and a substantial interest in estimating unbiased effects at the macro level:

- Random intercept at the level of country-years (and countries) to account for serial correlation due to clustering at the level of respondents (nested in country sampling points)
- Time dummies (=time FEs) to account for serial correlation due to time and common trends in the DV
 - Country dummies (=unit FEs) to account for unobserved heterogeneity related to country differences (e.g., institutional or historical differences) → makes estimates more reliable

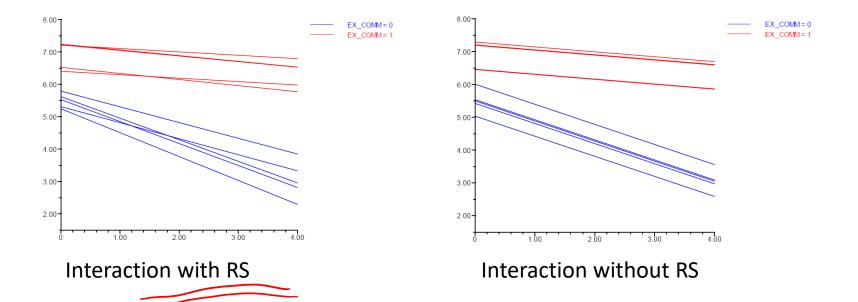
Group session #1

- You will be assigned to breakout rooms in three groups
- Each group scans through a text with complex multilevel structures, esp. the methods section in order to answer the following questions
 - 1. What is the outcome, and at which level is it measured
 - What is/are the core predictor variable(s), and at which level is it/ are they measured
 - How many levels exist and how is does the empirical design account for (different versions of) clustering? Please draw a diagram.
 - 4. Is unobserved heterogeneity addressed? If yes, how?

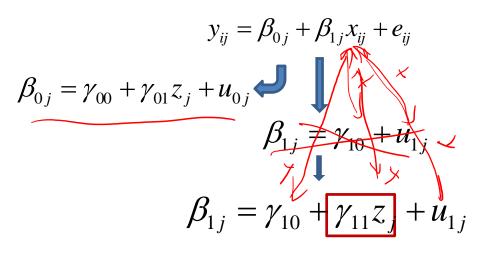
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- Interaction between context and individual variable
- Idea: Context feature explains different effect of individual feature across contexts (random slope)
- A priori (usually) identify significant random slope



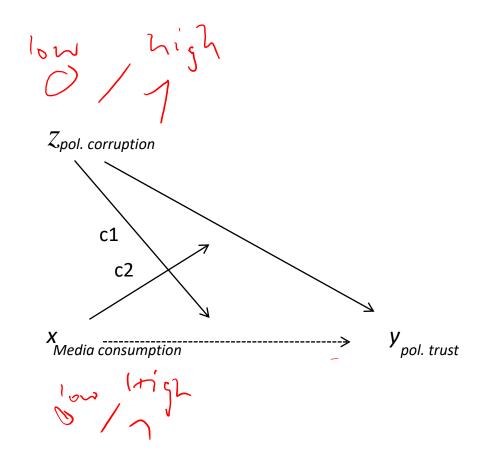
Specification of country-specific intercepts and slopes



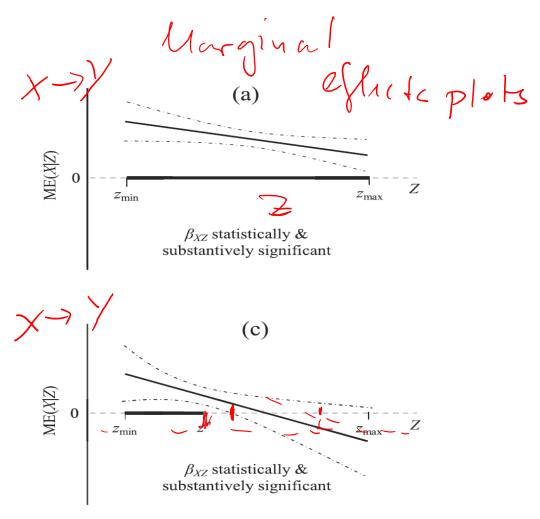
With interaction:

Overall notation
$$y_{ij} = \gamma_{00} + \gamma_{10}x_{ij} + \gamma_{01}z_{j} + \gamma_{11}x_{ij}z_{j} + u_{1j}x_{ij} + u_{0j} + e_{ij}$$
14.11.2021 Fixed Effects Random Part / Random Effects

- Hypotheses should be symmetrical (if theoretically reasonable)
 - H1: Political corruption reduces political trust, especially when media consumption is high. (c2)
 - H2: Media consumption reduces political trust, especially in contexts characterized by high political corruption. (c1))
- Statement on high and low values of the moderator often useful
 - H2a: In contexts with *high* political corruption, the relationship between media consumption and political trust is *negative*.
 - H2b: In contexts with *low* political corruption, the relationship between media consumption and political trust is *positive*.



- Always estimate both interaction term and unconditional effects in the model
- Symmetrical interpretation of the results along the hypotheses formulated
- Is the correlation significant for all values of the moderator? If not, what does this mean for the hypotheses?



Berry et al. 2012: 661

Stata

```
//Form interaction term beforehand
gen x z=x*z
mixed y \times z \times z \mid \mid id:
//better interact within the model per # (simplifies post-
estimation)
mixed y x z c.x#c.z ||id:
margins, dydx(x) at (z = (0 (0.1) 1))
marginsplot, yline(0)
margins, dydx(z) at (x = (0 (0.1) 1))
marginsplot, yline(0)
```

Centering

Version 1: At the overall mean or grand mean (also CGM)

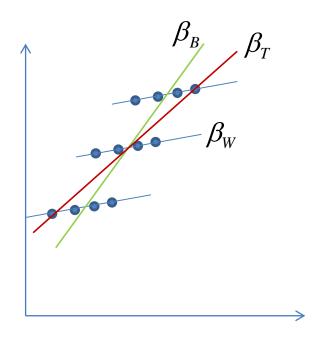
- Continuous variables receive a meaningful zero point
- Constant can be interpreted as an estimated value of the outcome for persons who have a mean expression on all characteristics
- All other parameter estimates remain identical (as in the uncentred case)
- Possibly reduces multicollinearity problems

Version 2: At the group mean (also CWC)

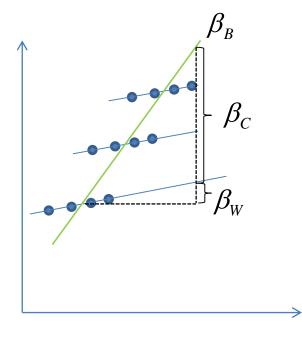
- Only for Level-1 variables
- Consequence: Between-group variance is removed from variable
- Constant is an estimate of the outcome for individuals who have all characteristics corresponding to their group mean

Changes correlation structure of the data; interpretation of coefficient estimates differs for level-2 variables

Context Effect of Group Mean



blue = Within-Effect green = Between-Effect red = Total Effect (mixed)



Between-Effect = Within-Effect + context effect

Centering and Effect Interpretation

Centering at the Grand Mean (CGM)

```
-Effect of x = \beta(within)

-Effect of \bar{x} (i.e., the group mean) = \beta(context)

-\beta(between) = \beta(within) + \beta(context)
```

Centering at the Group Mean (CWC)

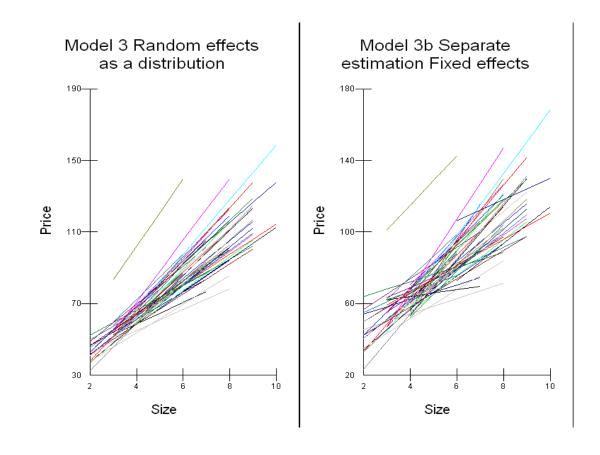
```
-Effect of x = \beta(within) [without "shrinkage"]

-Effect of \bar{x} (i.e., the group mean) = \beta(between)

-\beta(context) = \beta(between) - \beta(within)
```

Shrinkage

- Regression lines across individual contexts "shrink" towards the Grand Mean
- The fewer the observations at level 1, the stronger the shrinkage
- Certainty of estimation is to some extent borrowed from large clusters



from: Jones & Subramanian 2009, MlWin Traning Manual

Centering

When to center on the overall mean?

- Mostly useful, as it facilitates interpretation of the concept and context effects.
- If substantial interest in level 2 variable (or interaction at level 2), as it co-controls for composition effects of level 1.

When to center on the group mean?

- Substantive reasons: In the case of poorly comparable group means (e.g. center income at the country mean).
- If there is substantial interest in level 1 variables, as there is no shrinkage
- In the case of cross-level interaction → practically usually no difference compared to no centering

For level-1 interactions

Stata

```
//grand-mean
center UV1 UV2 , pre(cgm_) mean(mgm_)

//group-mean
bys id: center UV1 UV2 , pre(cwc_) mean(mwc_)

xtmixed AV cgm_UV1 cgm_UV2 ... ||id:
xtmixed AV cwc_UV1 cwc_UV2 ... ||id:
```

Group session #2

Last session, I asked you to prepare a description an interaction you are interested in. Introduce your interaction in pairs and discuss:

- Graphical representation
- What are the underlying hypotheses?
- What is an appropriate test, how would you proceed?

Which problems have you encountered (share them with others and me)?

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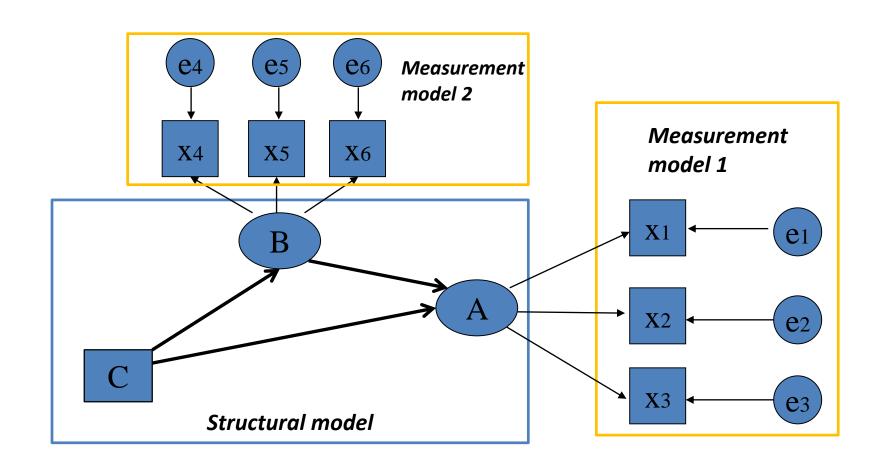
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Structural Equation Models

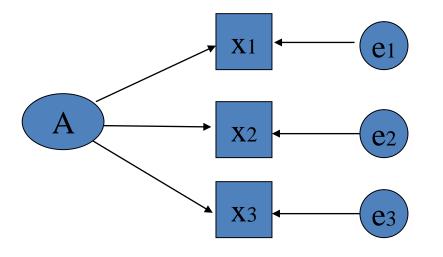
Structural Equation Models (= SEM)

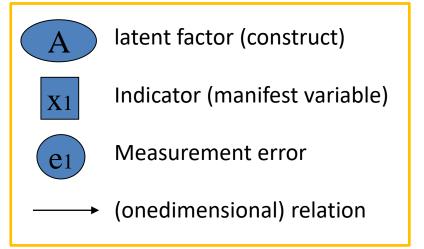
- consist of systems of equations
- can be divided into measurement models and structural models
- direct and indirect effects can be distinguished (mediation)
- distinguish between latent (non-measured) and manifest (measured) variables
- typical graphical representation of the models

Structural Equation Models

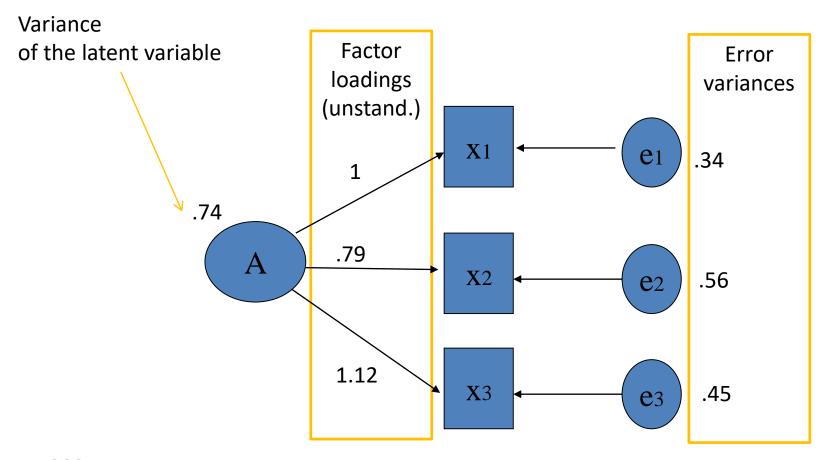


Measurement Model with one Factor

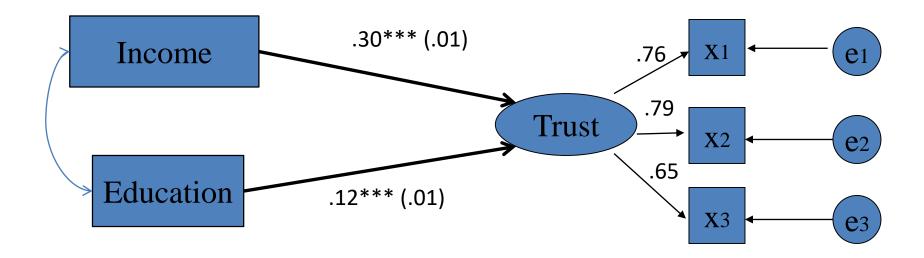




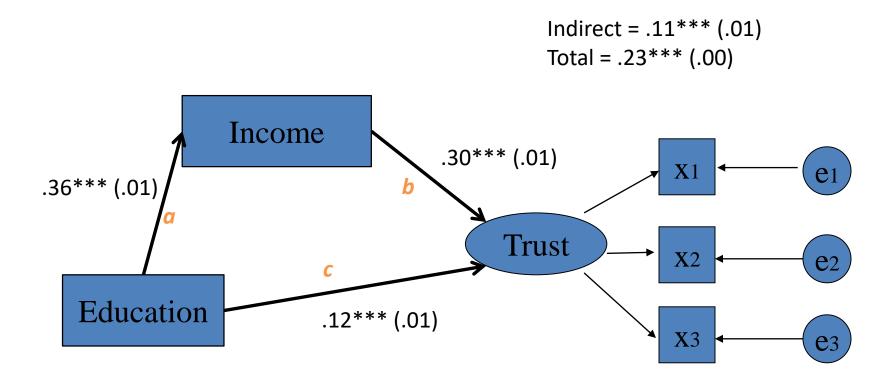
Measurement Model: Parameter (Loadings and variances)



Example 1: Social Trust



Example 2: Social Trust



Indirect effect of education = a * b

Total effect of education= indirect + direct effect or a * b + c

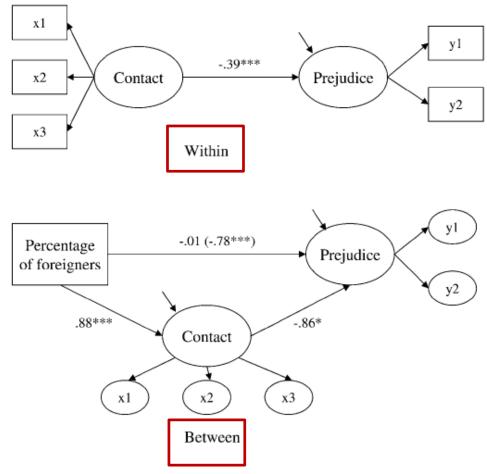
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Stata

```
* Example 1
sem (ppltrst pplfair pplhlp <- Trust) ///
(Trust <- income educyears) , latent(Trust) stand
estat gof , stats(all) // shows fit-indices

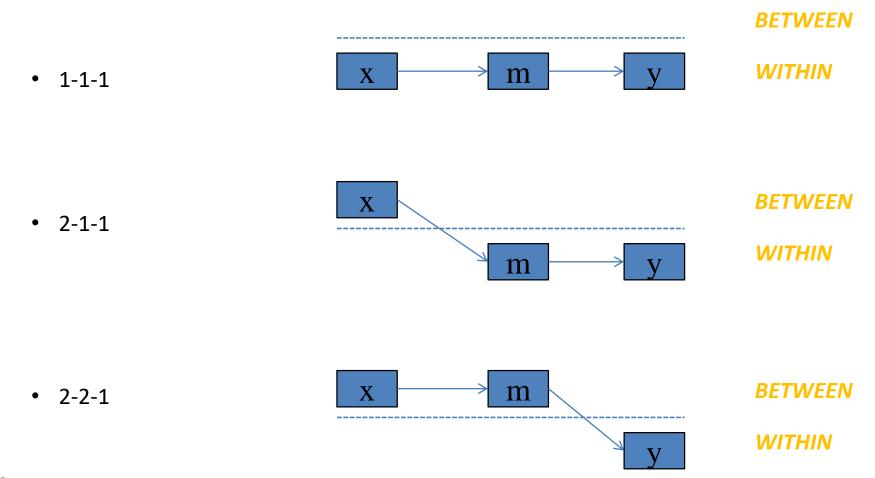
* Example 2
sem (ppltrst pplfair pplhlp <- Trust) ///
(Trust <- income educyears) ///
(income <- educyears) , latent(Trust) stand
estat teffects, stand //shows indirect effect
estat gof , stats(all)</pre>
```

Example Multi-Level SEM



Wagner, U., Christ, O., Pettigrew, T.F., Stellmacher, J., & Wolf, C. (2006). Prejudice and minority proportion: Contact instead of threat effects. *Social Psychology Quarterly*, *69*, 380-390.

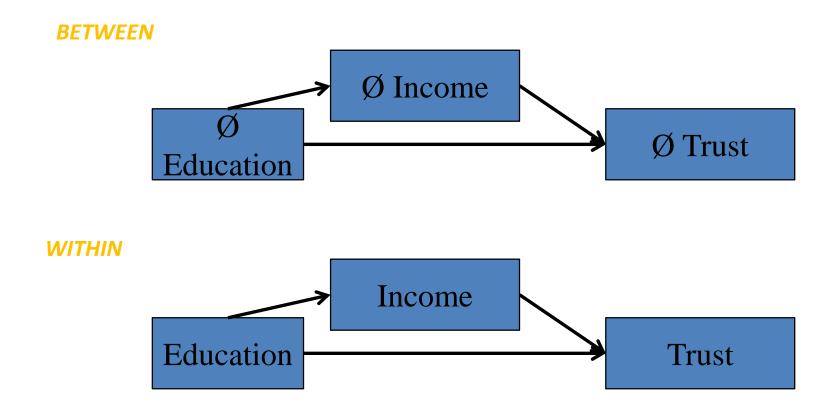
Typical Multi-Level SEM-Mediationmodel



Multi-Level SEM

- Without latent variables or mediation, multilevel regression and multilevel SEM produce equivalent results
- Latent measurement models (CFA) only reliable with large number of clusters (> 60)
- With multilevel mediation and level-2 involved, the between-level is one that is interpreted (Preacher et al. 2010)
- Mplus has enormous advantages over Stata in specifying ML-SEM models; Mplus syntax see http://www.quantpsy.org/pubs/syntax appendix 081311.pdf
- In R: lavaan package mimicks Mplus; Stata: gsem (slow and often does not converge)

Example 3: Social Trust on Individual and Country-Level

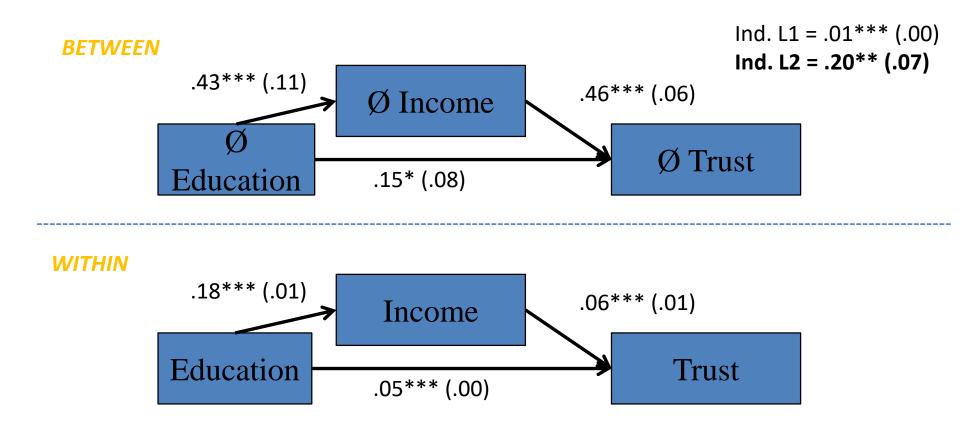


Mplus – Output

MODEL	RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
TRUST O	N			
INCOME	0.056	0.011	5.286	0.000
EDUCYEARS	0.046	0.004	11.346	0.000
INCOME O	N			
EDUCYEARS	0.177	0.009	20.568	0.000
Residual Variances				
TRUST	3.063	0.157	19.554	0.000
INCOME	3.487	0.193	18.066	0.000
Between Level				
TRUST O	N			
INCOME	0.458	0.062	7.443	0.000
EDUCYEARS	0.148	0.076	1.960	0.050
INCOME O	N			
EDUCYEARS	0.429	0.113	3.801	0.000
Intercepts				
TRUST	0.669	0.870	0.769	0.442
INCOME	1.022	1.342	0.761	0.447
Residual Variances				
TRUST	0.212	0.048	4.462	0.000
INCOME	1.646	0.614	2.681	0.007
New/Additional Parameters				
ITRUST	0.010	0.002	5.752	0.000
ITRUST2	0.196	0.070	2.814	0.005

Example 3: Social Trust on Individual- and Country – Level



Group session #3

Come together in groups and find examples for all three types of multilevel mediation:

Predictor-Mediator-Outcome

L1-L1-L1

L2-L1-L1

L2-L2-L1

Thank you for your Attention!