

## Einführung II

### Kontext und Mehr-Ebenen-Datensätze

## Warum?

- ▶ Moderne Erklärungen = Mehr-Ebenen-Erklärungen
- ▶ Viele Datensätze sind strukturiert (oder können so konstruiert werden)
- ▶ Statistische Mehr-Ebenen-Modelle können korrekte Koeffizienten/Standardfehler für Kontextwirkungen schätzen
- ▶ (Bilden nicht den komplexen Mechanismus ab)

# Was?

1. “random intercept”
2. “contextual effect”
3. “random slope”
4. “cross-level interaction”
5. “frog pond effects”
6. ... ?

# Wie?

- ▶ Einfache Regressionsmodelle vs
- ▶ Echte (statistische) Mehr-Ebenen-Modelle
- ▶ Letztere bauen auf den Regressionsmodellen auf, die Sie kennen

## “Pooling”

- ▶ (Beispiel: Politisches Vertrauen in 27 ESS-Ländern)
- ▶ Separate Analysen:
  - ▶ 27 Konstanten, 27 Sets von Koeffizienten
  - ▶ Keinerlei “pooling” der Daten - ineffizient

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  - ▶ Keinerlei “pooling” der Daten - ineffizient
- ▶ Eine gemeinsame Regressionsanalyse
  - ▶ 1 Konstante, 1 Set von Koeffizienten
  - ▶ Vollständiges “pooling” der Daten - bias, wenn sich Konstanten unterscheiden (Simpson's Paradox)

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  - ▶ 1 Konstante, 1 Set von Koeffizienten
  - ▶ Vollständiges “pooling” der Daten - bias, wenn sich Konstanten unterscheiden (Simpson's Paradox)
- ▶ Statistische Mehr-Ebenen-Modelle
  - ▶ Optimaler bzw. flexibler Kompromiß bei Kombination
  - ▶ “borrowing strength” - vor allem interessant, wenn wenige Personen pro Kontext und/oder große Unterschied in Personenzahl

## Simpson's Paradox: künstliche Daten

```
gen c= 1 in 1/4  
(52,344 missing values generated)  
replace c=2 in 5/8  
(4 real changes made)  
gen x=.  
(52,348 missing values generated)  
replace x = _n in 1/8  
(8 real changes made)  
gen y = 10 +2*x if c==1  
(52,344 missing values generated)  
replace y= -8 +2*x if c==2  
(4 real changes made)  
list c x y in 1/8, sep(4)
```

```
+-----+  
| c  x  y |  
+-----+  
1. | 1  1  12 |  
2. | 1  2  14 |  
3. | 1  3  16 |  
4. | 1  4  18 |  
+-----+  
5. | 2  5   2 |  
6. | 2  6   4 |  
7. | 2  7   6 |  
8. | 2  8   8 |  
+-----+
```



## Separate Regressionen

reg y x if c==1

Source	SS	df	MS	Number of obs	=	4
-----+						
Model	20	1	20	F(1, 2)	=	.
Residual	0	2	0	Prob > F	=	.
-----+						
Total	20	3	6.66666667	R-squared	=	1.0000
				Adj R-squared	=	1.0000
				Root MSE	=	0

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+					
x	2	.	.	.	.
_cons	10	.	.	.	.

reg y x if c==2

Source	SS	df	MS	Number of obs	=	4
-----+						
Model	20	1	20	F(1, 2)	=	.
Residual	0	2	0	Prob > F	=	.
-----+						
Total	20	3	6.66666667	R-squared	=	1.0000
				Adj R-squared	=	1.0000
				Root MSE	=	0

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+					
x	2	.	.	.	.
_cons	-8	.	.	.	.

## Gemeinsame Regressionen

reg y x

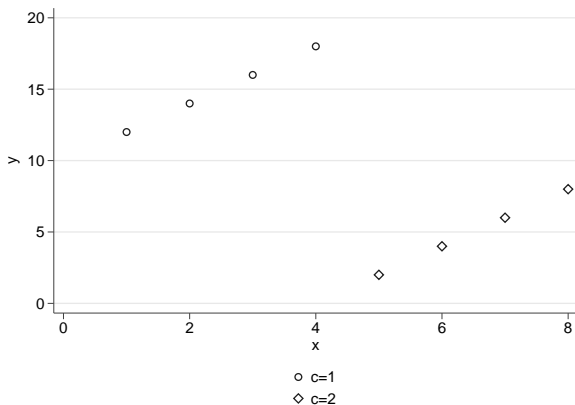
Source	SS	df	MS	Number of obs	=	8
Model	85.7142857	1	85.7142857	F(1, 6)	=	3.33
Residual	154.285714	6	25.7142857	Prob > F	=	0.1177
				R-squared	=	0.3571
				Adj R-squared	=	0.2500
Total	240	7	34.2857143	Root MSE	=	5.0709

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x	-1.428571	.7824608	-1.83	0.118	-3.343184 .4860412
_cons	16.42857	3.951233	4.16	0.006	6.760252 26.09689

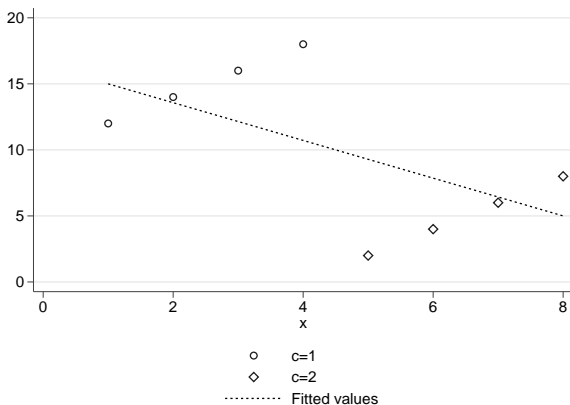
# Plot I

```
graph twoway (scatter y x if c==1) (scatter y x if c==2) , legend(label(1 "c=1") label(2 "c=2"))  
graph export plot1.pdf , replace
```



## Plot II

```
graph twoway (scatter y x if c==1) (scatter y x if c==2) (lfit y x) , legend(label(1 "c=1") label(2 "c=2"))  
graph export plot2.pdf , replace
```



## Was geht noch?

- ▶ Mehr als zwei Ebenen
- ▶ Cross-classification → mehr dazu nächste Woche

## Wie schätzt man das?

- ▶ Lineare Regressionsmodelle - OLS
- ▶ Nicht-lineare Modelle - Maximum Likelihood (Forschungsmethoden VL)
- ▶ Für *alle* Mehr-Ebenen-Modelle: Maximum Likelihood oder vergleichbare/verwandte Verfahren
  - ▶ Numerisch extrem aufwendig
  - ▶ Nicht-lineare Mehr-Ebenen-Modelle möglich (logit, count etc.)

# Stata I

- ▶ Früher spezielle Software (MLWin, HLM) oder Stata-Addons notwendig
- ▶ Heute gängige Modelle mit Stata schätzbar
  - ▶ Dokumentation
  - ▶ Geschwindigkeit + Stabilität
  - ▶ Transaktionskosten + Werkzeuge
- ▶ (xt)mixed

## Stata II

`mixed` lineare Regression

`me(qr)logit` binäres Logit-Modell

`meologit` ordinales Logit-Modell

`me(qr)poisson`, `menbreg` Count-Modelle

`gsem` (u.a.) multinomiales Logit-Modell



# Trust

- ▶ Interpersonelles Vertrauen (Sozialkapital) → *Institutionenvertrauen* (Easton)
- ▶ 27 ESS-Länder (Welle 5)

## Einfaches Modell, komplettes pooling, keine cluster

```
set more off
use ml-exercise-ess-5 , replace
* komplettes pooling
reg poltrust ppltrst
```

Source	SS	df	MS	Number of obs	=	49,780
-----+-----				F(1, 49778)	=	7675.01
Model	34520.391	1	34520.391	Prob > F	=	0.0000
Residual	223889.722	49,778	4.49776452	R-squared	=	0.1336
-----+-----				Adj R-squared	=	0.1336
Total	258410.113	49,779	5.19114714	Root MSE	=	2.1208

poltrust	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
ppltrst	.3396662	.0038772	87.61	0.000	.3320669	.3472654
_cons	1.719947	.0211187	81.44	0.000	1.678554	1.76134
-----+-----						

```
* complete cases markieren, damit empty models vergleichbar sind
gen sample = e(sample)
```

## Einfaches Modell, komplettes pooling, aber cluster

```
use ml-exercise-ess-5 , replace
* komplettes pooling
reg poltrust ppltrst, cluster(cntry)
```

```
Linear regression                Number of obs   =   49,780
                                F(1, 26)         =   121.45
                                Prob > F             =   0.0000
                                R-squared            =   0.1336
                                Root MSE         =   2.1208
```

(Std. Err. adjusted for 27 clusters in cntry)

```
-----+-----
            |               Robust
    poltrust |               Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
    ppltrst |    .3396662   .0308209    11.02  0.000   .2763128   .4030195
    _cons   |    1.719947   .1623116    10.60  0.000   1.386311   2.053583
-----+-----
```

```
est store cluster
```

## Einfaches Modell, kein pooling

```
* kein pooling
bysort centry: reg poltrust ppltrst
```

```
-----
-> centry = BE
```

Source	SS	df	MS	Number of obs	=	1,670
-----						
Model	734.921522	1	734.921522	F(1, 1668)	=	213.62
Residual	5738.47044	1,668	3.44033	Prob > F	=	0.0000
-----						
Total	6473.39196	1,669	3.87860513	R-squared	=	0.1135
-----						
				Adj R-squared	=	0.1130
				Root MSE	=	1.8548

poltrust	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----					
ppltrst	.317986	.0217564	14.62	0.000	.2753132 .3606588
_cons	2.459308	.1188338	20.70	0.000	2.226229 2.692387

```
-----
-> centry = BG
```

Source	SS	df	MS	Number of obs	=	2,291
-----						
Model	407.068824	1	407.068824	F(1, 2289)	=	98.89
Residual	9422.33512	2,289	4.11635436	Prob > F	=	0.0000
-----						
Total	9829.40394	2,290	4.29231613	R-squared	=	0.0414
-----						
				Adj R-squared	=	0.0410
				Root MSE	=	2.0289

# Einfaches Modell, country fixed effects (dummies)

```

use ml-exercise-ess-5 , replace
* country fixed effects
encode cntry , gen(numbercountry)
reg poltrst ppltrst i.numbercountry, cluster(cntry)

Linear regression              Number of obs   =    49,780
                              F(0, 26)        =          .
                              Prob > F              =          .
                              R-squared             =    0.2866
                              Root MSE        =    1.925

-----+-----
                               (Std. Err. adjusted for 27 clusters in cntry)
-----+-----
      |                               |
      |                               | Robust
      |                               | Std. Err.
      |                               | t      P>|t|
      |                               | [95% Conf. Interval]
-----+-----
      |                               |
      | poltrst |      Coef.      | |
|---|---|---|
      | ppltrst |      .2308962   |
      |         |      .0122556   |
      |         |      18.84      |
      |         |      0.000      |
      |         |      .2057045   |
      |         |      .2560878   |
      |         |-----|-----|
      | numbercountry |
      |-----|-----|-----|-----|-----|-----|
      | BG |      -1.575482 |
      |   |      .0193904 |
      |   |      -81.25    |
      |   |      0.000     |
      |   |      -1.61534 |
      |   |      -1.535625 |
      | CH |      .9980999 |
      |   |      .0077862 |
      |   |      128.19    |
      |   |      0.000     |
      |   |      .9820942 |
      |   |      1.014104 |
      | CY |      .0876725 |
      |   |      .0135978 |
      |   |      6.45      |
      |   |      0.000     |
      |   |      .0597219 |
      |   |      .1156232 |
      | CZ |      -1.080142 |
      |   |      .0069017 |
      |   |      -156.50  |
      |   |      0.000     |
      |   |      -1.094328 |
      |   |      -1.065955 |
      | DE |      -.4013071 |
      |   |      .0048993 |
      |   |      -81.91    |
      |   |      0.000     |
      |   |      -.4113778 |
      |   |      -.3912364 |
      | DK |      .8750523 |
      |   |      .0223549 |
      |   |      39.14     |
      |   |      0.000     |
      |   |      .8291012 |
      |   |      .9210034 |
      | EE |      -.4639403 |
      |   |      .008079   |
      |   |      -57.43    |
      |   |      0.000     |
      |   |      -.4805468 |
      |   |      -.4473337 |
      | ES |      -.8381794 |
      |   |      .0011337 |
      |   |      -739.33   |
      |   |      0.000     |
      |   |      -.8405098 |
      |   |      -.8358491 |
      | FI |      .3830721 |
      |   |      .0179687 |
      |   |      21.32     |
      |   |      0.000     |
      |   |      .3461369 |
      |   |      .4200072 |
      | FR |      -.4243839 |
      |   |      .0088638 |
      |   |      47.88     |
      |   |      0.000     |
      |   |      -.4426036 |
      |   |      -.4061642 |
      | GB |      -.4842493 |
      |   |      .0039486 |
      |   |      -122.64   |
      |   |      0.000     |
      |   |      -.4923657 |
      |   |      -.4761329 |
      | GR |      -2.238518 |
      |   |      .0124577 |
      |   |      -179.69   |
      |   |      0.000     |
      |   |      -2.264125 |
      |   |      -2.212911 |
      | HR |      -2.080213 |
      |   |      .006917   |
      |   |      -351.57   |
      |   |      0.000     |
      |   |      -2.092376 |
      |   |      -2.068051 |
      | HU |      -.4384424 |
      |   |      .006987   |
      |   |      -62.75    |
      |   |      0.000     |
      |   |      -.4528045 |
      |   |      -.4240803 |
      | IE |      -.8429582 |
      |   |      .0004863 |
      |   |      -1733.49  |
      |   |      0.000     |
      |   |      -.8439578 |
      |   |      -.8419587 |
      | IL |      -.9373666 |
      |   |      .0018617 |
      |   |      -503.50   |
      |   |      0.000     |
      |   |      -.9411934 |
      |   |      -.9335398 |
      | LT |      -1.755159 |
      |   |      .003691   |
      |   |      -475.53   |
      |   |      0.000     |
      |   |      -1.762746 |
      |   |      -1.747572 |
      | NL |      .9773006 |
      |   |      .0117304 |
      |   |      83.31     |
      |   |      0.000     |
      |   |      .9531884 |
      |   |      1.001413 |
      | NO |      .8609662 |
      |   |      .0201895 |
      |   |      42.64     |
      |   |      0.000     |
      |   |      .8194659 |
      |   |      .9024664 |
      | PL |      -1.053559 |
      |   |      .0081462 |
      |   |      -129.55   |
      |   |      0.000     |
      |   |      -1.072104 |
      |   |      -1.038615 |
      | PT |      -1.438542 |
      |   |      .0162507 |
      |   |      -88.52    |
      |   |      0.000     |
      |   |      -1.471946 |
      |   |      -1.405139 |
      | RU |      -.6123425 |
      |   |      .0111056 |
      |   |      -55.14    |
      |   |      0.000     |
      |   |      -.6351703 |
      |   |      -.5895146 |
      | SE |      1.129833 |
      |   |      .016004   |
      |   |      70.60     |
      |   |      0.000     |
      |   |      1.096937 |
      |   |      1.16273 |
      | SI |      -1.315145 |
      |   |      .0136442 |
      |   |      -96.39    |
      |   |      0.000     |
      |   |      -1.343191 |
      |   |      -1.287099 |
      | SK |      -.7962383 |
      |   |      .0129253 |
      |   |      -61.60    |
      |   |      0.000     |
      |   |      -.8228066 |
      |   |      -.76967 |
      | UA |      -1.872426 |
      |   |      .0110316 |
      |   |      -169.73   |
      |   |      0.000     |
      |   |      -1.895102 |
      |   |      -1.849751 |
      |         |-----|-----|
      | _cons |      2.898929 |
      |         |      .0618649 |
      |         |      46.86     |
      |         |      0.000     |
      |         |      2.771764 |
      |         |      3.026095 |
      |         |-----|-----|
  
```

est store fixedeffects

## Multi-level: Empty Model

```
mixed poltrust || cntry: if sample, nolog
```

```
Mixed-effects ML regression      Number of obs   =   49,780
Group variable: cntry           Number of groups =    27
```

```
Obs per group:
  min =    990
  avg =  1,843.7
  max =  2,933
```

```
Wald chi2(0) = .
Log likelihood = -105112.39      Prob > chi2 = .
```

```
-----+-----
      poltrust |      Coef.   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      _cons |  3.465337   .2184091   15.87   0.000   3.037263   3.893411
-----+-----
```

```
-----+-----
Random-effects Parameters |   Estimate   Std. Err.    [95% Conf. Interval]
-----+-----
cntry: Identity          |
var(_cons) |  1.285686   .350563     .7534269   2.19396
-----+-----
var(Residual) |  3.981859   .0252459    3.932684   4.031649
-----+-----
```

```
LR test vs. linear model: chibar2(01) = 13029.14      Prob >= chibar2 = 0.0000
est store empty
```

# ICC

- ▶ “Intraclass Correlation Coefficient”
- ▶ Varianz der Residuen auf der Kontextebene (random intercepts)  
/ Varianz der Residuen auf der Kontextebene + Varianz der Residuen auf der Individualebene
- ▶ Schätzung für die Korrelation zufälliger Einflüsse zwischen zwei Personen aus demselben Kontext - Ähnlichkeit

```
estat icc
```

```
Intraclass correlation
```

Level	ICC	Std. Err.	[95% Conf. Interval]	
cntry	.2440769	.0503215	.1590897	.3552833

## Auch das geht: Empty-Model mit drei Ebenen

```

mixed poltrust || cntry: || ess5_reg: if sample, nolog

Mixed-effects ML regression              Number of obs   =   49,780

-----+-----
|      No. of      Observations per Group
Group Variable |      Groups  Minimum  Average  Maximum
-----+-----
cntry |          27      990   1,843.7   2,933
  ess5_reg |          326         5   152.7     2,117
-----+-----

Wald chi2(0)          =          .
Log likelihood = -104861.96          Prob > chi2          =          .

-----+-----
poltrust |      Coef.  Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
  _cons |  3.451006   .2195123    15.72  0.000    3.02077   3.881243
-----+-----

Random-effects Parameters |   Estimate  Std. Err.    [95% Conf. Interval]
-----+-----
cntry: Identity          |
var(_cons) |  1.280021   .3529922    .7455569   2.197625
-----+-----
ess5_reg: Identity      |
var(_cons) |  .1088999   .0131177    .0859993   .1378987
-----+-----
var(Residual) |  3.909241   .0248672    3.860805   3.958285
-----+-----

LR test vs. linear model: chi2(2) = 13530.00          Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.
est store empty3
  
```



# Modell mit Individualvariable + random intercept

```
mixed poltrust ppltrst, nolog || cntry:
```

```
Mixed-effects ML regression      Number of obs   =   49,780
Group variable: cntry            Number of groups =    27
```

```
Obs per group:
  min =    990
  avg =  1,843.7
  max =    2,933
```

```
Wald chi2(1)      =   3722.74
Log likelihood = -103317.84      Prob > chi2      =   0.0000
```

```
-----+-----
      poltrust |      Coef.   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      ppltrst |   .2311844   .003789    61.01  0.000    .223758   .2386107
      _cons   |   2.329236   .1858588   12.53  0.000    1.964959   2.693512
-----+-----
```

```
-----+-----
Random-effects Parameters |   Estimate   Std. Err.    [95% Conf. Interval]
-----+-----
cntry: Identity          |
var(_cons) |   .9211896   .2513747    .5396009   1.572626
-----+-----
var(Residual) |   3.705399   .0234931    3.659638   3.751732
-----+-----
```

```
LR test vs. linear model: chibar2(01) = 9480.09      Prob >= chibar2 = 0.0000
est store randomi
```

# Modell mit Individualvariable, random intercept und Kontextvariable (corruption protection)

```
mixed poltrust ppltrst c_ticpi_2009, nolog || cntry:
```

```
Mixed-effects ML regression      Number of obs   =   49,780
Group variable: cntry            Number of groups =    27
```

```
Obs per group:
  min =      990
  avg =   1,843.7
  max =    2,933
```

```
Wald chi2(2)      =   3793.57
Log likelihood = -103303.55      Prob > chi2      =   0.0000
```

```
-----+-----
      poltrust |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      ppltrst |   .231046   .0037889    60.98  0.000   .2236199   .2384721
c_ticpi_2009 |   .3776843  .053013    7.12  0.000   .2737806   .4815879
      _cons |  -.0467665  .3509429   -0.13  0.894   -.734602   .641069
-----+-----
```

```
-----+-----
Random-effects Parameters | Estimate Std. Err.   [95% Conf. Interval]
-----+-----
cntry: Identity          |
var(_cons) |   .3184155  .0872196    .186138   .544695
-----+-----
var(Residual) |   3.705398  .0234931    3.659637   3.75173
-----+-----
```

```
LR test vs. linear model: chibar2(01) = 4087.44      Prob >= chibar2 = 0.0000
est store randomikon
```

# Modell mit Individualvariablen, random intercept, Kontextvariable (corruption protection) + random slope ppltrst

```
mixed poltrust ppltrst c_ticpi_2009, nolog || cntry: ppltrst

Mixed-effects ML regression           Number of obs   =   49,780
Group variable: cntry                 Number of groups =    27

Obs per group:
  min =      990
  avg =   1,843.7
  max =    2,933

Wald chi2(2) =      398.93
Log likelihood = -103214.01           Prob > chi2     =    0.0000
```

```
-----+-----
poltrust |      Coef.   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
ppltrst | .2366623   .0122872   19.26  0.000   .2125798   .2607447
c_ticpi_2009 | .2791271   .0566023    4.93  0.000   .1681887   .3900655
  _cons | .5105324   .3730705    1.37  0.171  -.2206724   1.241737
-----+-----
```

```
-----+-----
Random-effects Parameters |      Estimate   Std. Err.    [95% Conf. Interval]
-----+-----
cntry: Independent
var(ppltrst) | .0036517   .0011126   .0020097   .006635
var(_cons) | .3521383   .0990664   .2028833   .6111956
-----+-----
var(Residual) | 3.687217   .0233846   3.641668   3.733336
-----+-----
```

```
LR test vs. linear model: chi2(2) = 4266.51           Prob > chi2 = 0.0000
```

Note: LR test is conservative and provided only for reference.  
 est store randomikonrandoms

## Modelle im Überblick

```
est tab cluster empty empty3 randomi randomikon randomikonrandoms
```

Variable	cluster	empty	empty3	randomi	randomikon	randomikons
-						
ppltrst	.33966617					
_cons	1.7199469					
poltrust						
ppltrst				.23118438	.23104601	.23666226
c_ticpi_2009					.37768426	.2791271
_cons		3.4653374	3.4510065	2.3292358	-.0467665	.51053239
lns1_1_1						
_cons		.12564621	.1234383	-.04104472	-.57219903	-2.806288
lnsig_e						
_cons		.69087439	.68167165	.65489542	.65489528	.65243604
lns2_1_1						
_cons			-1.1086631			
lns1_1_2						
_cons						-.52186567

## Sparsamkeit und Fit

```
est stats cluster empty empty3 randomi randomikon randomikonrandoms
```

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
cluster	49,780	-111627	-108057.9	2	216119.8	216137.4
empty	49,780	.	-105112.4	3	210230.8	210257.2
empty3	49,780	.	-104862	4	209731.9	209767.2
randomi	49,780	.	-103317.8	4	206643.7	206678.9
randomikon	49,780	.	-103303.5	5	206617.1	206661.2
randomikon~s	49,780	.	-103214	6	206440	206492.9

Note: N=Obs used in calculating BIC; see [R] BIC note.

## Fazit

- ▶ Mit Stata lassen sich Mehr-Ebenen-Modelle schätzen ...
- ▶ ... die komplizierter als die meisten unserer Theorien sein können
- ▶ Meist keine spezielle Software nötig

## Ausblick

- ▶ Nächste Woche: Was tun mit Multiple-Country Repeated Cross-Sectional Designs?
- ▶ Dann: viele *Anwendungen*
- ▶ Fragen?