

**Model Implied Instrumental
Variable (MIIIV) Methods using
MIIIVsem:
An R Package for Structural
Equation Models (SEMs)**

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INTRODUCTION

System Wide Maximum Likelihood (ML)

- Pure, ideal ML estimator properties
 - Consistent
 - Asymptotic unbiased
 - Asymptotic efficient
 - Asymptotic normality
 - Asymptotic standard errors

INTRODUCTION

System Wide Maximum Likelihood (ML)

- If your models are perfectly specified & your observed variables are from normal distributions, then
 - Go home, no need to attend workshop

INTRODUCTION

System Wide Maximum Likelihood (ML)

- If your models are *approximations* & your observed variables are from *nonnormal* distributions, then
 - You've come to right place
 - Approximations undermine ML properties
 - Bias & inconsistent estimator likely
 - Efficiency & accurate standard errors no longer guaranteed

INTRODUCTION

Other Issues with ML

- Underidentified models
 - Can prevent estimation & testing even if key equations in system are identified
- Nonconvergence
 - Prevent estimates from being obtained
 - Increasing iterations often does not help

INTRODUCTION

Other Issues with ML

- Spread bias from bad parts of model to good parts even in well specified equations
- Global tests of fit often significant
 - Not always easy to find source of problem
 - Bad measurement model?
 - Bad latent variable model?
 - Both?

INTRODUCTION

What do we need?

1. Estimator less likely to spread structural specification errors throughout system
2. Local estimates of equations
3. Local tests of equations
4. Ability to estimate identified equations, even if whole model not identified
5. Ideally a "distribution free" estimator
6. Noniterative without convergence problems

INTRODUCTION

Model Implied Instrumental Variables (MIIVs) addresses these:

1. MIIV-2SLS less likely to spread structural specification errors throughout system
2. Local estimates of equations
3. Local tests of equations
4. Ability to estimate identified equations, even if whole model not identified
5. A "distribution free" estimator
6. Noniterative without convergence problems

INTRODUCTION

Purposes

1. Give an overview of MIIV-2SLS
2. Show you how to download the MIIVsem R package
3. Present and illustrate the primary steps in using MIIVsem
4. Teach you how to use & interpret MIIVsem input & output
5. Provide empirical examples that are estimated and tested with MIIVsem

Installing MIIVsem

First steps

- Install MIIVsem Version 0.5.2
- Install lavaan
 - Will use for simulating data and estimating models later
- Type the following commands into the R console

```
install.packages( "MIIVsem" )  
install.packages( "lavaan" )
```

Loading MIIIVsem

Next, load MIIIVsem

- Type the following command:

```
library( "MIIIVsem" )
```

- Will load lavaan later when needed

Inputting Data File

First dataset is Bollen (1989)

- Comes with MIIVsem
- Accessed by typing `bollen1989a` in R console

To match the examples in the workshop we'll save the `bollen1989a` as `data` and rename the variables.

Inputting Data File

```
# save the political democracy
# dataset as data.
data <- bollen1989a

# rename the variables.
colnames(data) <- c("Z4", "Z5", "Z6",
                    "Z7", "Z8", "Z9",
                    "Z10", "Z11", "Z1",
                    "Z2", "Z3" )
```

PRIMARY INGREDIENTS

1. Specify Model
2. Transform Latent to Observed (L2O) variable model
3. Find Model Implied Instrumental Variables (MIIVs, pronounced to rhyme with "gives")
4. Estimate with Two Stage Least Squares (2SLS)
5. Test each overidentified equation

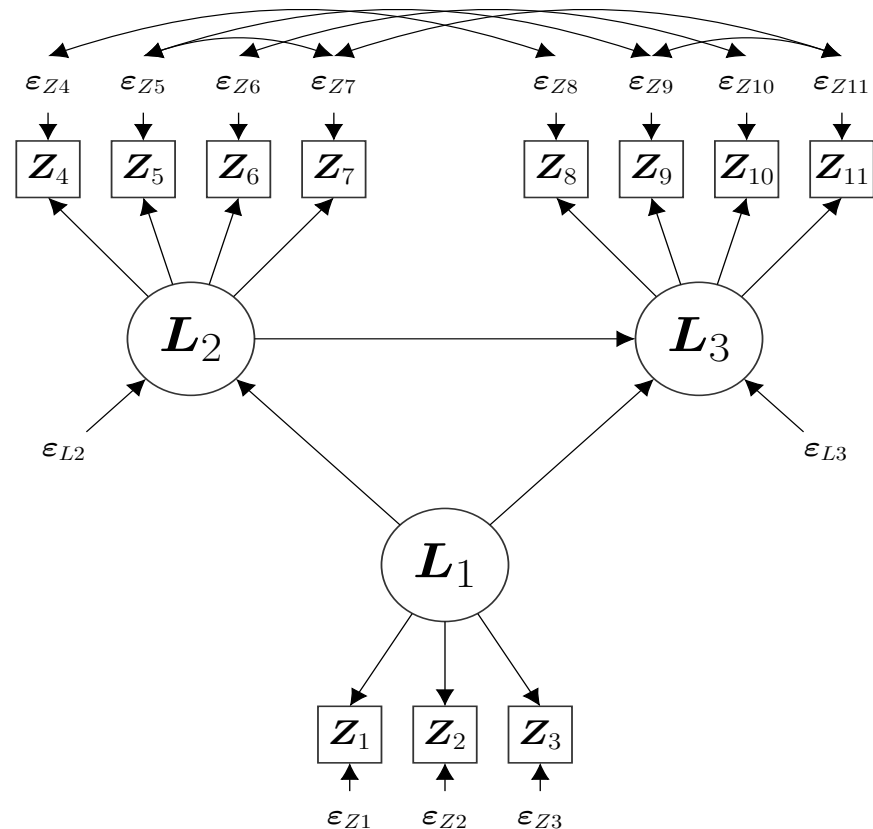
PRIMARY INGREDIENTS

1. Specify Model

- Researcher lays out the latent variable and measurement models

Industrialization and Political Democracy Example

L_1 = Industrialization at time 1
 L_2 = Political Democracy at time 1
 L_3 = Political Democracy at time 2
 Z_1 to Z_{11} are indicators of L_1 to L_3



Industrialization and Political Democracy Example

Latent Variable Model

$$L_1 = \varepsilon_{L_1}$$

$$L_2 = \alpha_{L_2} + B_{21}L_1 + \varepsilon_{L_2}$$

$$L_3 = \alpha_{L_3} + B_{31}L_1 + B_{32}L_2 + \varepsilon_{L_3}$$

Measurement Model

$$Z_1 = L_1 + \varepsilon_{z1}$$

$$Z_2 = \Lambda_{21}L_1 + \varepsilon_{z2}$$

$$Z_3 = \Lambda_{31}L_1 + \varepsilon_{z3}$$

$$Z_4 = L_2 + \varepsilon_{z4}$$

$$Z_5 = \Lambda_{52}L_2 + \varepsilon_{z5}$$

$$Z_6 = \Lambda_{62}L_2 + \varepsilon_{z6}$$

$$Z_7 = \Lambda_{72}L_2 + \varepsilon_{z7}$$

$$Z_8 = L_3 + \varepsilon_{z8}$$

$$Z_9 = \Lambda_{93}L_3 + \varepsilon_{z9}$$

$$Z_{10} = \Lambda_{10,3}L_3 + \varepsilon_{z10}$$

$$Z_{11} = \Lambda_{11,3}L_3 + \varepsilon_{z11}$$

MIIVsem: Model Syntax

Main ingredient of MIIVsem:

- Model
- To define, for search or estimation, MIIVsem uses lavaan (Rosseel, 2012) syntax

Major operators to define relationships in model:

=~ "measured by" e.g., $L1 =~ Z1$

~ "regressed on" e.g., $L5 ~ L4$

~~ "covaries with" e.g., $L2~~L3$

* Assigns equality or numerical constraints

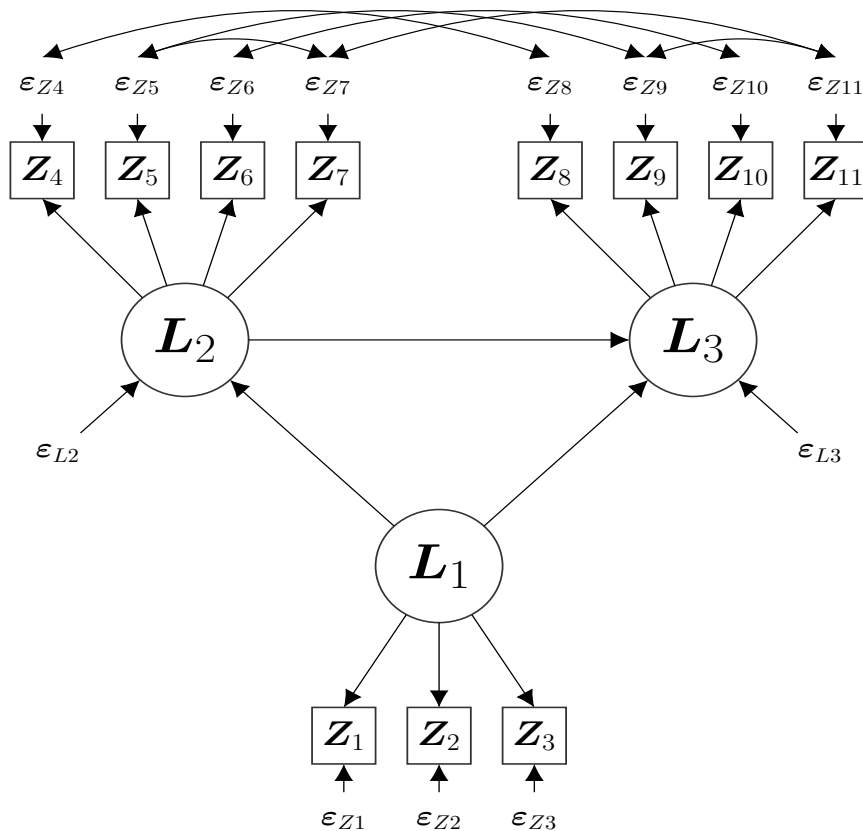
e.g., $L4~ b*L3+b*L2$ OR $L1=~1*Z1+.5*Z2+Z3$

MIIVsem: Industrialization-Democracy Example

In **R**, `<-` is used for assignment. Below we specify the industrialization-democracy model using our model syntax operators, surrounding the equations in single quotes. This creates an object in our workspace named `model.indem1`

```
model.indem1 <- '  
  L1 =~ Z1 + Z2 + Z3  
  L2 =~ Z4 + Z5 + Z6 + Z7  
  L3 =~ Z8 + Z9 + Z10 + Z11  
  
  L2 ~ L1  
  L3 ~ L1 + L2  
  
  Z4 ~~ Z8  
  Z5 ~~ Z7 + Z9  
  Z6 ~~ Z10  
  Z7 ~~ Z11  
  Z9 ~~ Z11 '
```

EXERCISE: In R, specify the model below.



```
model.indem1 <- '
  L1 =~ Z1 + Z2 + Z3
  L2 =~ Z4 + Z5 + Z6 + Z7
  L3 =~ Z8 + Z9 + Z10 + Z11

  L2 ~ L1
  L3 ~ L1 + L2

  Z4 ~~ Z8
  Z5 ~~ Z7 + Z9
  Z6 ~~ Z10
  Z7 ~~ Z11
  Z9 ~~ Z11
'
```

PRIMARY INGREDIENTS

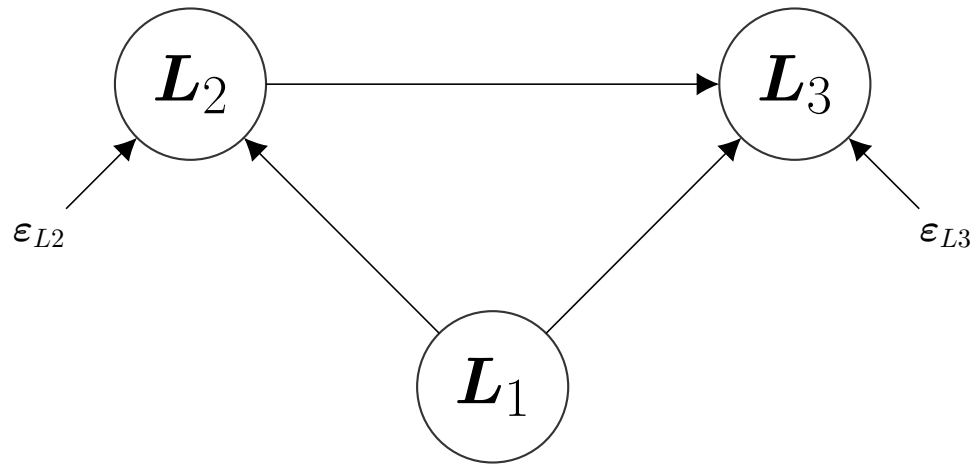
1. Specify Model ✓
2. Transform Latent to Observed (L2O) variable model
3. Find Model Implied Instrumental Variables (MIIVs, pronounced to rhyme with "gives")
4. Estimate with Two Stage Least Squares (2SLS)
5. Test each overidentified equation

PRIMARY INGREDIENTS

1. Specify Model ✓
2. Transform Latent to Observed (L2O) variable model (Bollen, 1996)
 - MIIVsem does this automatically
 - Here we illustrate how MIIVsem does it

PRIMARY INGREDIENTS

2. Transform Latent to Observed (L2O) variable model (Bollen, 1996)



PRIMARY INGREDIENTS

2. Transform Latent to Observed (L2O) variable model

$$L_1 = \varepsilon_{L_1}$$

$$L_2 = \alpha_{L_2} + B_{21}L_1 + \varepsilon_{L_2}$$

$$L_3 = \alpha_{L_3} + B_{31}L_1 + B_{32}L_2 + \varepsilon_{L_3}$$

$$Z_1 = L_1 + \varepsilon_{z1}$$

$$Z_4 = L_2 + \varepsilon_{z4}$$

$$Z_8 = L_3 + \varepsilon_{z8}$$

$$L_1 = Z_1 - \varepsilon_{z1}$$

$$L_2 = Z_4 - \varepsilon_{z4}$$

$$L_3 = Z_8 - \varepsilon_{z8}$$

PRIMARY INGREDIENTS

2. Transform Latent to Observed (L2O) variable model

Substitute scaling indicator minus error for each latent variable:

$$L_2 = \alpha_{L2} + B_{21}L_1 + \varepsilon_{L2} \Rightarrow$$

$$\boxed{Z_4 = \alpha_{L2} + B_{21}Z_1 + u_4} \text{ with } u_4 = -B_{21}\varepsilon_{Z1} + \varepsilon_{Z4} + \varepsilon_{L2}$$

$$L_3 = \alpha_{L3} + B_{31}L_1 + B_{32}L_2 + \varepsilon_{L3} \Rightarrow$$

$$\boxed{Z_8 = \alpha_{L3} + B_{31}Z_1 + B_{32}Z_4 + u_8} \text{ with } u_8 = -B_{31}\varepsilon_{Z1} - B_{32}\varepsilon_{Z4} + \varepsilon_{Z8} + \varepsilon_{L3}$$

Latent variable equations are transformed into
observed variable equations with composite errors.

Industrialization and Political Democracy Example

Latent Variable Model

$$L_1 = \varepsilon_{L_1}$$

$$L_2 = \alpha_{L_2} + B_{21}L_1 + \varepsilon_{L_2}$$

$$L_3 = \alpha_{L_3} + B_{31}L_1 + B_{32}L_2 + \varepsilon_{L_3}$$

Measurement Model

$$Z_1 = L_1 + \varepsilon_{z1}$$

$$Z_2 = \Lambda_{21}L_1 + \varepsilon_{z2}$$

$$Z_3 = \Lambda_{31}L_1 + \varepsilon_{z3}$$

$$Z_4 = L_2 + \varepsilon_{z4}$$

$$Z_5 = \Lambda_{52}L_2 + \varepsilon_{z5}$$

$$Z_6 = \Lambda_{62}L_2 + \varepsilon_{z6}$$

$$Z_7 = \Lambda_{72}L_2 + \varepsilon_{z7}$$

$$Z_8 = L_3 + \varepsilon_{z8}$$

$$Z_9 = \Lambda_{93}L_3 + \varepsilon_{z9}$$

$$Z_{10} = \Lambda_{10,3}L_3 + \varepsilon_{z10}$$

$$Z_{11} = \Lambda_{11,3}L_3 + \varepsilon_{z11}$$

EXERCISE: Do the L2O transformation for Z_5 .

2. Transform Latent to Observed (L2O) variable model

Measurement Model

$$Z_1 = L_1 + \varepsilon_{z1}$$

$$Z_2 = \Lambda_{21}L_1 + \varepsilon_{z2}$$

$$Z_3 = \Lambda_{31}L_1 + \varepsilon_{z3}$$

$$Z_4 = L_2 + \varepsilon_{z4}$$

$$Z_5 = \Lambda_{52}L_2 + \varepsilon_{z5}$$

$$Z_6 = \Lambda_{62}L_2 + \varepsilon_{z6}$$

$$Z_7 = \Lambda_{72}L_2 + \varepsilon_{z7}$$

$$Z_8 = L_3 + \varepsilon_{z8}$$

$$Z_9 = \Lambda_{93}L_3 + \varepsilon_{z9}$$

$$Z_{10} = \Lambda_{10,3}L_3 + \varepsilon_{z10}$$

$$Z_{11} = \Lambda_{11,3}L_3 + \varepsilon_{z11}$$

Find L2O Transformation for: $Z_5 = \Lambda_{52}L_2 + \varepsilon_{z5}$

SOLUTION: Do the L2O transformation for Z_5 .

SOLUTION: Do the L2O transformation for Z_5 .

PRIMARY INGREDIENTS

2. Transform Latent to Observed (L2O) variable model

Same problem for previous latent variable L2O transformation:

$$L_2 = \alpha_{L2} + B_{21}L_1 + \varepsilon_{L2} \Rightarrow$$

$$\boxed{Z_4 = \alpha_{L2} + B_{21}Z_1 + u_4} \text{ with } u_4 = -B_{21}\varepsilon_{Z1} + \varepsilon_{Z4} + \varepsilon_{L2}$$

$$L_3 = \alpha_{L3} + B_{31}L_1 + B_{32}L_2 + \varepsilon_{L3} \Rightarrow$$

$$\boxed{Z_8 = \alpha_{L3} + B_{31}Z_1 + B_{32}Z_4 + u_8} \text{ with } u_8 = -B_{31}\varepsilon_{Z1} - B_{32}\varepsilon_{Z4} + \varepsilon_{Z8} + \varepsilon_{L3}$$

PRIMARY INGREDIENTS

2. Transform Latent to Observed (L2O) variable model

$$Z_4 = \alpha_{L2} + B_{21}Z_1 + u_4 \text{ with } u_4 = -B_{21}\epsilon_{Z1} + \epsilon_{Z4} + \epsilon_{L2}$$

$$Z_8 = \alpha_{L3} + B_{31}Z_1 + B_{32}Z_4 + u_8 \text{ with } u_8 = -B_{31}\epsilon_{Z1} - B_{32}\epsilon_{Z4} + \epsilon_{Z8} + \epsilon_{L3}$$

Problem: error correlates with Right Hand Side (RHS) Z s, OLS biased
Instrumental variables can help.

1. Correlate with RHS Z s
2. Not correlate with composite errors
3. At least as many instruments as RHS Z s

Finding suitable instruments is the next step in MIIV-2SLS.

PRIMARY INGREDIENTS

1. Specify Model ✓
2. Transform Latent to Observed (L2O) variable model ✓
3. Find Model Implied Instrumental Variables (MIIVs, pronounced to rhyme with "gives")
4. Estimate with Two Stage Least Squares (2SLS)
5. Tests each overidentified equation

PRIMARY INGREDIENTS

3. Find Model Implied Instrumental Variables (MIIVs)

- Instrumental variables help obtain consistent & asymptotic unbiased estimates of coefficients
 - Useful when equation error correlates with explanatory variables
 - Addresses situation where OLS does not work
- Researchers typically search for instrumental variable external to model
- My approach: MIIVs

PRIMARY INGREDIENTS

3. Find Model Implied Instrumental Variables (MIIVs)

- Key property of instruments is that they are uncorrelated with equation error
- MIIV approach proposed in Bollen (1996) finds instruments among observed variables already part of model
 - If identified model, then MIIVs are generally part of model
 - No need to search outside of model
 - Structure of model implies which observed variables are uncorrelated with equation disturbance

PRIMARY INGREDIENTS

3. Find Model Implied Instrumental Variables (MIIVs)

General algorithm to find MIIVs (Bollen, 1996)

1. Focus on single equation
2. Find direct & indirect effects on the observed variables of each error in the composite error,
3. Eliminate the observed variables found in 2.,
4. Find the direct & indirect effects of any errors correlated with the composite error,
5. Eliminate the observed variables found in 4.,
6. Remaining observed variables are MIIVs.

PRIMARY INGREDIENTS

3. Find Model Implied Instrumental Variables (MIIVs)

- MIIVsem finds MIIVs automatically
 - R: MIIVsem (Fisher, Bollen, Gates & Rönkkö)
- Useful to illustrate process with examples

PRIMARY INGREDIENTS

3. Find Model Implied Instrumental Variables (MIIVs)

Consider first latent variable equation, latent political democracy (L_2) regressed on latent industrialization (L_1):

$$L_2 = \alpha_{L2} + B_{21}L_1 + \varepsilon_{L2} \Rightarrow$$

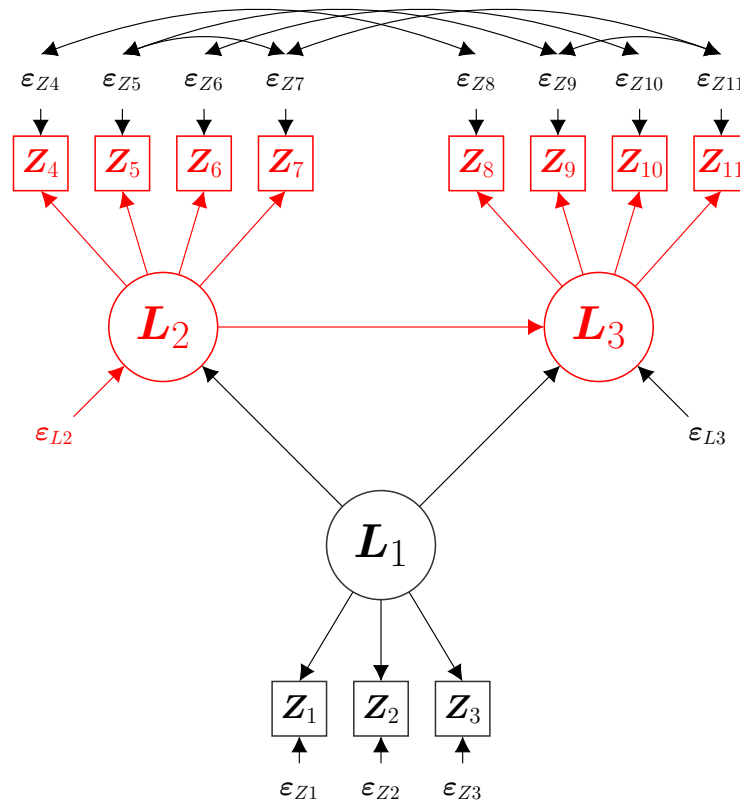
$$\boxed{Z_4 = \alpha_{L2} + B_{21}Z_1 + u_4} \text{ with } u_4 = -B_{21}\varepsilon_{Z1} + \varepsilon_{Z4} + \varepsilon_{L2}$$

1. Find direct & indirect effects on observed variables of $\varepsilon_{Z1}, \varepsilon_{Z4}, \varepsilon_{L2}$.

Let's start with ε_{L2} and return to path diagram of model.

PRIMARY INGREDIENTS

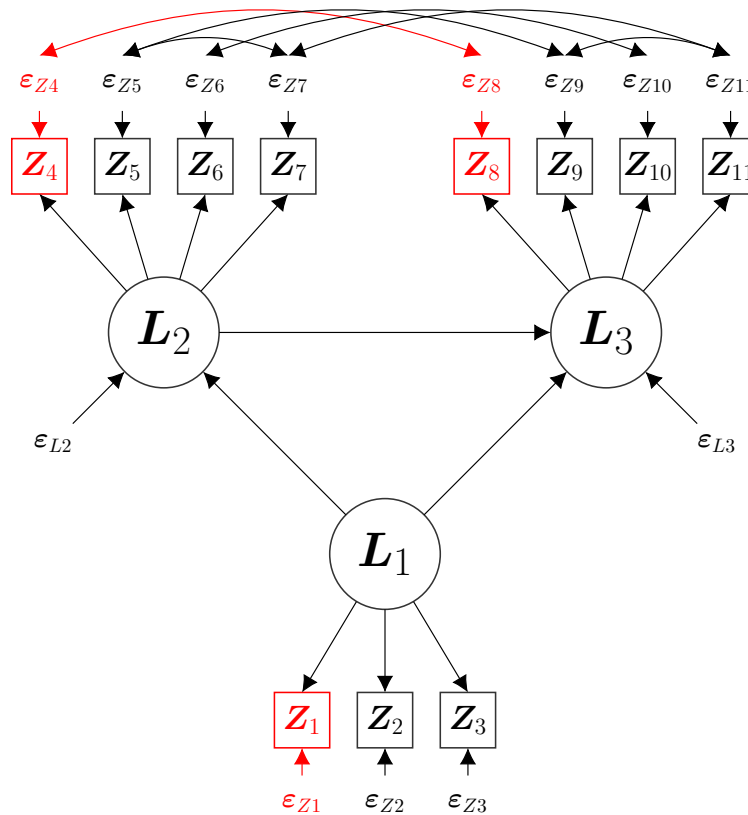
Find direct & indirect effects of ε_{L2}



Only variables NOT eliminated by ε_{L2} are Z_1, Z_2, Z_3 .

PRIMARY INGREDIENTS

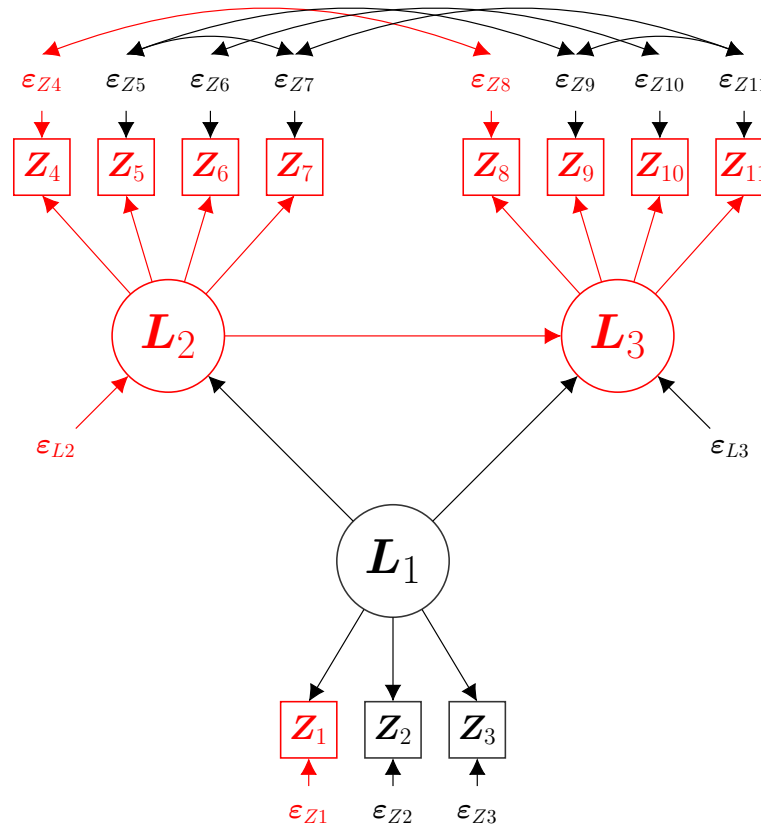
Find direct & indirect effects of $\varepsilon_{Z_1}, \varepsilon_{Z_4}$



Eliminates Z_1, Z_4 , and Z_8 as MIIVs.

PRIMARY INGREDIENTS

Find direct & indirect effects of $\epsilon_{Z_1}, \epsilon_{Z_4}, \epsilon_{L_2}$



Z_2, Z_3 only MIIVs.

EXERCISE: Find the MIIVs for the Z_5 equation.

3. Find Model Implied Instrumental Variables (MIIVs)

- Return to previous L2O transformation

$$Z_4 = L_2 + \varepsilon_{z4} \Rightarrow L_2 = Z_4 - \varepsilon_{z4}$$

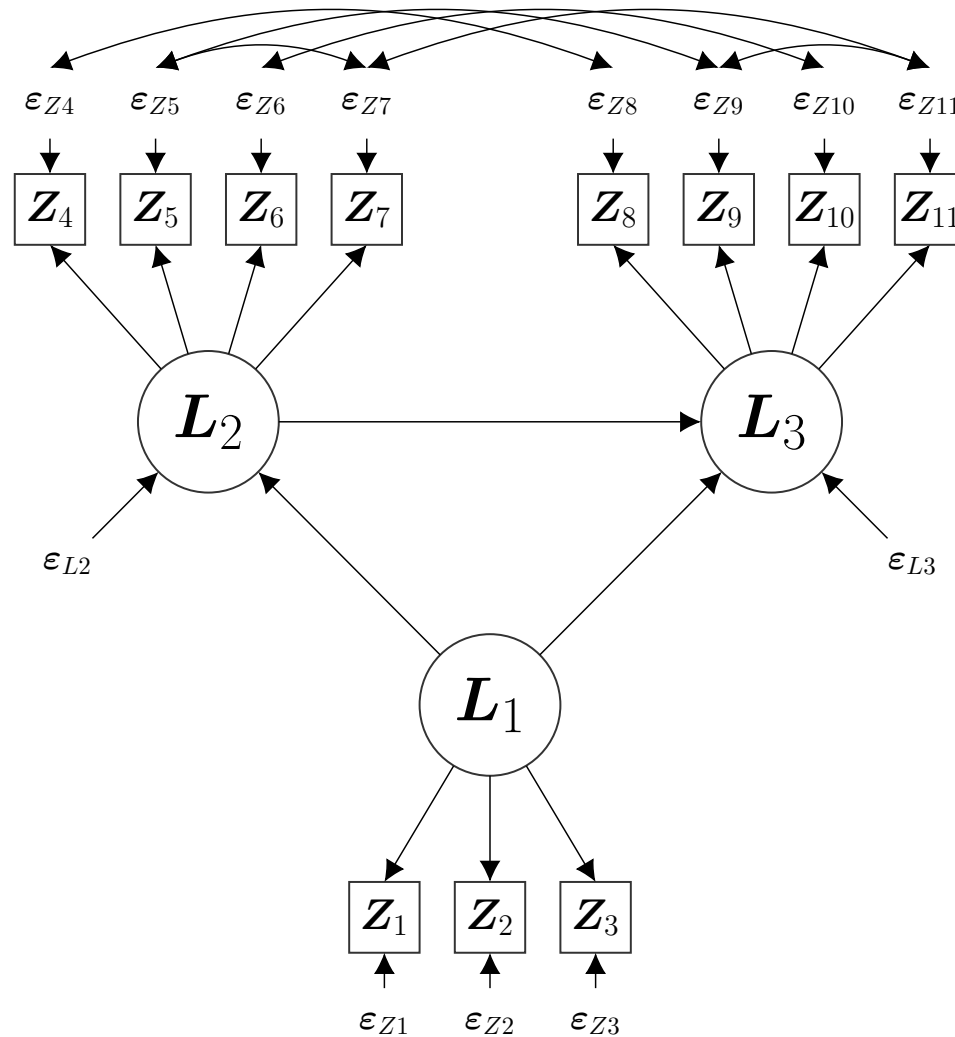
$$\boxed{Z_5 = \Lambda_{52}L_2 + \varepsilon_{z5}} \Rightarrow Z_5 = \Lambda_{52}Z_4 - \Lambda_{52}\varepsilon_{z4} + \varepsilon_{z5}$$

Find any variable directly or indirectly influenced by ε_{z4} or ε_{z5} and eliminate as MIIV.

Find any errors that correlate with ε_{z4} or ε_{z5}

Eliminate as MIIVs any variable these influence.

EXERCISE: Find the MIIVs for the Z_5 equation.



SOLUTION: Find the MIIVs for the Z_5 equation.

SOLUTION: Find the MIIVs for the Z_5 equation.

The `miivs()`, or `MIIV_search`, function in `MIIVsem` automatically performs the MIIV search.

The only argument needed to run `miivs()` is `model`.

```
model.indem1 <- '  
  L1 =~ Z1 + Z2 + Z3  
  L2 =~ Z4 + Z5 + Z6 + Z7  
  L3 =~ Z8 + Z9 + Z10 + Z11
```

```
  
  L2 ~ L1  
  L3 ~ L1 + L2
```

```
  
  Z4 ~~ Z8  
  Z5 ~~ Z7 + Z9  
  Z6 ~~ Z10  
  Z7 ~~ Z11  
  Z9 ~~ Z11  '
```

```
miivs(model.indem1)
```

EXERCISE: Use MIIVsem for the MIIV search.

The `miivs()`, or `MIIV_search`, function in `MIIVsem` automatically performs the MIIV search.

```
model.indem1 <- '  
  L1 =~ Z1 + Z2 + Z3  
  L2 =~ Z4 + Z5 + Z6 + Z7  
  L3 =~ Z8 + Z9 + Z10 + Z11  
  
  L2 ~ L1  
  L3 ~ L1 + L2  
  
  Z4 ~~ Z8  
  Z5 ~~ Z7 + Z9  
  Z6 ~~ Z10  
  Z7 ~~ Z11  
  Z9 ~~ Z11  '
```

```
miivs(model.indem1)
```

The only argument needed to run `miivs()` is `model`.

Using the earlier defined model for industrialization-democracy run the MIIV search and check your output to see if it matches the output on the following slide.

Output:

```
## Model Equation Information
##
##   LHS  RHS      MIIVs
##   Z2   Z1      Z4, Z5, Z6, Z7, Z9, Z3, Z8, Z10, Z11
##   Z3   Z1      Z4, Z5, Z6, Z7, Z9, Z2, Z8, Z10, Z11
##   Z5   Z4      Z6, Z1, Z2, Z3, Z10, Z11
##   Z6   Z4      Z5, Z7, Z9, Z1, Z2, Z3, Z11
##   Z7   Z4      Z6, Z9, Z1, Z2, Z3, Z10
##   Z9   Z8      Z6, Z7, Z1, Z2, Z3, Z10
##   Z10  Z8      Z5, Z7, Z9, Z1, Z2, Z3, Z11
##   Z11  Z8      Z5, Z6, Z1, Z2, Z3, Z10
##   Z4   Z1      Z2, Z3
##   Z8   Z1, Z4  Z5, Z6, Z7, Z2, Z3
```

Note: The `summary` method for `miivs` objects provides additional options for displaying the MIIV search information.

PRIMARY INGREDIENTS

1. Specify Model ✓
2. Transform Latent to Observed (L2O) variable model ✓
3. Find Model Implied Instrumental Variables (MIIVs) ✓
4. Estimate with Two Stage Least Squares (2SLS)
5. Tests each overidentified equation

PRIMARY INGREDIENTS

4. Estimate with Two Stage Least Squares (2SLS)

In general,

\mathbf{Y}_j = vector containing values of j th dependent variable for L2O equation

\mathbf{Z}_j = matrix of explanatory variables on RHS of same j th L2O equation

\mathbf{V}_j = matrix of MIVs for same j th L2O equation

2SLS estimator of coefficients is $(\hat{\mathbf{Z}}_j' \hat{\mathbf{Z}}_j)^{-1} \hat{\mathbf{Z}}_j' \mathbf{Y}_j$

where $\hat{\mathbf{Z}}_j = \mathbf{V}_j (\mathbf{V}_j' \mathbf{V}_j)^{-1} \mathbf{V}_j' \mathbf{Z}_j$

Noniterative

No issues with convergence

PRIMARY INGREDIENTS

4. Estimate with Two Stage Least Squares (2SLS)

Consider first latent variable equation, latent political democracy (L_2)
regressed on latent industrialization (L_1):

$$L_2 = \alpha_{L_2} + B_{21}L_1 + \varepsilon_{L_2} \Rightarrow \boxed{Z_4 = \alpha_{L_2} + B_{21}Z_1 + u_4} \quad \text{MIVs are: } Z_2, Z_3$$

$$\mathbf{Y}_j = \begin{bmatrix} Z_{41} \\ Z_{42} \\ \vdots \\ Z_{4N} \end{bmatrix} \quad \mathbf{Z}_j = \begin{bmatrix} 1 & Z_{11} \\ 1 & Z_{12} \\ \vdots & \vdots \\ 1 & Z_{1N} \end{bmatrix} \quad \mathbf{V}_j = \begin{bmatrix} 1 & Z_{21} & Z_{31} \\ 1 & Z_{22} & Z_{32} \\ \vdots & \vdots & \vdots \\ 1 & Z_{2N} & Z_{3N} \end{bmatrix}$$

2SLS estimator of coefficients is $(\hat{\mathbf{Z}}_j' \hat{\mathbf{Z}}_j)^{-1} \hat{\mathbf{Z}}_j' \mathbf{Y}_j$

where $\hat{\mathbf{Z}}_j = \mathbf{V}_j (\mathbf{V}_j' \mathbf{V}_j)^{-1} \mathbf{V}_j' \mathbf{Z}_j$

PRIMARY INGREDIENTS

4. Estimate with Two Stage Least Squares (2SLS)

Comparison	MIIV-2SLS	ML
Consistency	✓	✓
Asymp. unbiased	✓	✓
Asymp. normal	✓	✓
Asymp. efficient	✓*	✓
Asymp. s.e.	✓	✓
Noniterative	✓	-
Nonnormal robust	✓	-**
No SEM software needed	✓	-
Overidentification test	equation	model

*2SLS efficient among limited information estimators.

**Corrected significance tests available.

PRIMARY INGREDIENTS

4. Estimate with Two Stage Least Squares (2SLS)

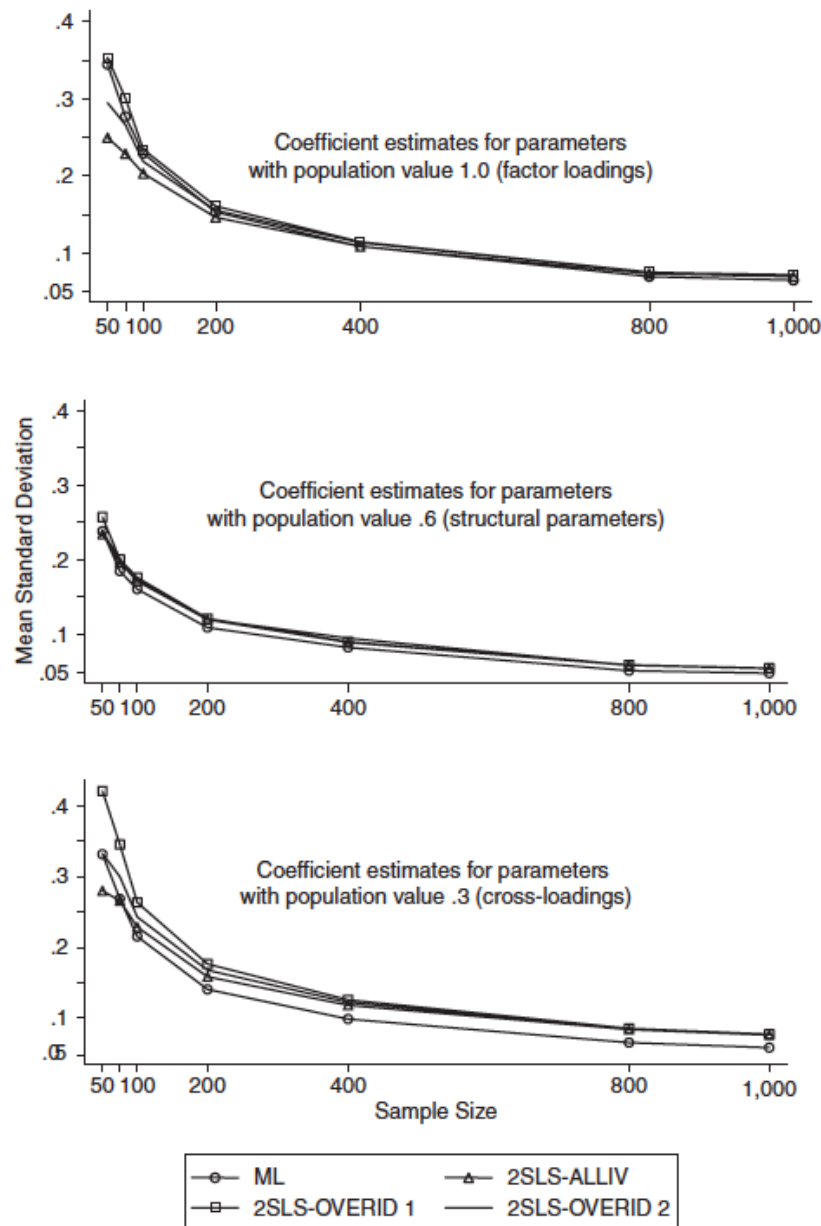
Illustration of ML and MLIV-2SLS simulation Bollen, Kirby, Curran, Paxton, & Chen (2007)

Graph on next page gives standard deviation of parameters under ideal conditions for ML:

Normality

Correct specification

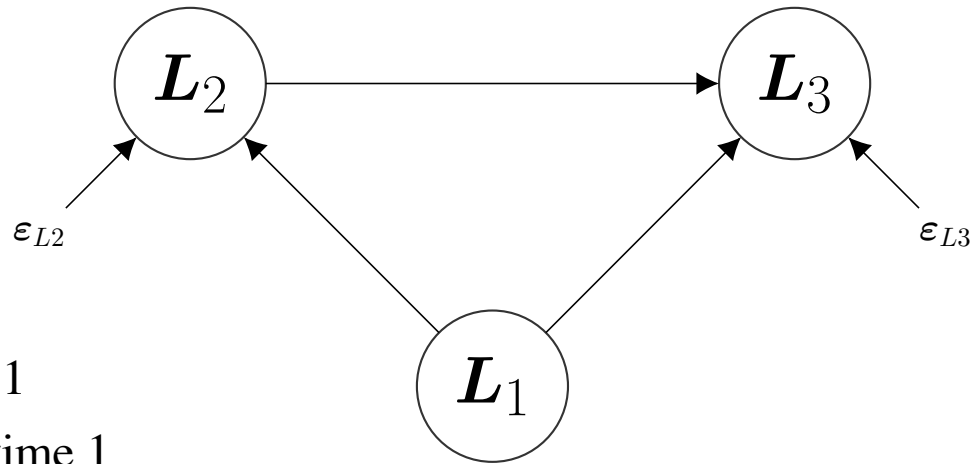
Mean Standard Deviation of Estimates From Four Estimators by Sample Size for Parameter Estimates From Specification 1, the Correctly Specified Model



PRIMARY INGREDIENTS

4. Estimate with Two Stage Least Squares (2SLS)

- Return to latent variable model for example



L_1 = Industrialization at time 1

L_2 = Political Democracy at time 1

L_3 = Political Democracy at time 2

PRIMARY INGREDIENTS

`miive()`

- MIV estimation function in MIVsem
- Use `miive()` to estimate the industrialization-democracy example using MIV-2SLS.
- “data” is name assigned to the industrialization-democracy example
- Next slide recaps all the steps for estimation for industrialization-democracy example.
 - Already loaded MIVsem, renamed the data and specified the model,
 - Only step left is to run `miive`.

EXERCISE: Estimate the Industrialization-Democracy model.

```
model.indem1 <- '  
  L1 =~ Z1 + Z2 + Z3  
  L2 =~ Z4 + Z5 + Z6 + Z7  
  L3 =~ Z8 + Z9 + Z10 + Z11  
  
  L2 ~ L1  
  L3 ~ L1 + L2  
  
  Z4 ~~ Z8  
  Z5 ~~ Z7 + Z9  
  Z6 ~~ Z10  
  Z7 ~~ Z11  
  Z9 ~~ Z11  '  
  
data <- bollen1989a  
colnames(data) <- c("Z4", "Z5", "Z6", "Z7",  
                    "Z8", "Z9", "Z10", "Z11",  
                    "Z1", "Z2", "Z3")  
miive(model.indem1, data)
```


MIIVsem: Header for estimation output.

Number of observations: *the number of observations used for all equations in the system.*

Number of equations: *the total number of L2O equations estimated.*

Estimator: *the estimator used, either MIIV-2SLS or PIV.*

```
## MIIVsem (0.5.2) results
##
## Number of observations          75
## Number of equations            10
## Estimator                      MIIV-2SLS
## Standard Errors                standard
## Missing                        listwise
```

MIIVsem: Header for estimation output.

Standard errors: *the method used to compute standard errors, this will be discussed again when we discuss the bootstrap.*

Missing: *listwise is the default. In our dataset there was no missing data, this can be verified by looking at the number of observations.*

```
## MIIVsem (0.5.2) results
##
## Number of observations              75
## Number of equations                10
## Estimator                         MIIV-2SLS
## Standard Errors                   standard
## Missing                           listwise
```

PRIMARY INGREDIENTS

Parameter Estimates:

##

##

STRUCTURAL COEFFICIENTS:

##		Estimate	Std.Err	z-value	P(> z)	Sargan	df	P(Chi)
##	L1 =~							
##	Z1	1.000						
##	Z2	2.078	0.128	16.171	0.000	8.301	8	0.405
##	Z3	1.751	0.149	11.782	0.000	8.738	8	0.365
##	L2 =~							
##	Z4	1.000						
##	Z5	1.139	0.179	6.371	0.000	8.409	5	0.135
##	Z6	0.969	0.140	6.924	0.000	5.874	6	0.437
##	Z7	1.210	0.139	8.713	0.000	4.276	5	0.510
##	L3 =~							
##	Z8	1.000						
##	Z9	1.051	0.165	6.377	0.000	8.712	5	0.121
##	Z10	1.180	0.151	7.814	0.000	9.538	6	0.146
##	Z11	1.203	0.154	7.798	0.000	2.795	5	0.731
##								
##	L2 ~							
##	L1	1.261	0.426	2.962	0.003	0.503	1	0.478
##	L3 ~							
##	L1	1.123	0.312	3.598	0.000	0.801	3	0.849
##	L2	0.724	0.101	7.140	0.000			

PRIMARY INGREDIENTS

INTERCEPTS:

##		Estimate	Std.Err	z-value	P(> z)
##	L2	-0.909	2.170	-0.419	0.675
##	L3	-4.499	1.424	-3.160	0.002
##	Z1	0.000			
##	Z10	0.135	0.830	0.163	0.870
##	Z11	-2.137	0.853	-2.505	0.012
##	Z2	-5.711	0.654	-8.727	0.000
##	Z3	-5.292	0.758	-6.985	0.000
##	Z4	0.000			
##	Z5	-1.969	1.044	-1.886	0.059
##	Z6	1.265	0.814	1.553	0.120
##	Z7	-2.160	0.814	-2.654	0.008
##	Z8	0.000			
##	Z9	-2.418	0.909	-2.659	0.008

PRIMARY INGREDIENTS

1. Specify Model ✓
2. Transform Latent to Observed (L2O) variable model ✓
3. Find Model Implied Instrumental Variables (MIIVs) ✓
4. Estimate w/ Two Stage Least Squares (2SLS) ✓
5. Tests each overidentified equation

PRIMARY INGREDIENTS

5. Tests each overidentified equation

$$\frac{\hat{\mathbf{u}}' \mathbf{V} (\mathbf{V}' \mathbf{V})^{-1} \mathbf{V}' \hat{\mathbf{u}}}{\hat{\mathbf{u}}' \hat{\mathbf{u}} / N} \sim \chi^2$$

where

$\hat{\mathbf{u}}$ = 2SLS residuals

\mathbf{V} = MIIVs

N = sample size

df = # MIIVs - # endogenous regressors

PRIMARY INGREDIENTS

5. Tests each overidentified equation

Sargan Test:

H_0 : MIIVs uncorrelated with equation error

H_a : At least 1 MIIIV correlates with error

Reject H_0 is evidence against model because model led to MIIVs.

PRIMARY INGREDIENTS

Parameter Estimates:

##

##

STRUCTURAL COEFFICIENTS:

##		Estimate	Std.Err	z-value	P(> z)	Sargan	df	P(Chi)
##	L1 =~							
##	Z1	1.000						
##	Z2	2.078	0.128	16.171	0.000	8.301	8	0.405
##	Z3	1.751	0.149	11.782	0.000	8.738	8	0.365
##	L2 =~							
##	Z4	1.000						
##	Z5	1.139	0.179	6.371	0.000	8.409	5	0.135
##	Z6	0.969	0.140	6.924	0.000	5.874	6	0.437
##	Z7	1.210	0.139	8.713	0.000	4.276	5	0.510
##	L3 =~							
##	Z8	1.000						
##	Z9	1.051	0.165	6.377	0.000	8.712	5	0.121
##	Z10	1.180	0.151	7.814	0.000	9.538	6	0.146
##	Z11	1.203	0.154	7.798	0.000	2.795	5	0.731
##								
##	L2 ~							
##	L1	1.261	0.426	2.962	0.003	0.503	1	0.478
##	L3 ~							
##	L1	1.123	0.312	3.598	0.000	0.801	3	0.849
##	L2	0.724	0.101	7.140	0.000			

EXERCISE: Adjust Sargan Test for multiple comparisons.

Multiple testing problem

- `sarg.adjust` argument of the `miive()`
 - p-value adjustment method for the Sargan test.

Reestimate the industrialization-democracy example

- Use Holm ("holm") correction for multiple comparisons
- Compare p-values to unadjusted counterparts

```
miive(model.indem1, data, sarg.adjust = "holm")
```

PRIMARY INGREDIENTS

Parameter Estimates:

##

##

STRUCTURAL COEFFICIENTS:

##		Estimate	Std.Err	z-value	P(> z)	Sargan	df	P(Chi)
##	L1 =~							
##	Z1	1.000						
##	Z2	2.078	0.128	16.171	0.000	8.301	8	1.000
##	Z3	1.751	0.149	11.782	0.000	8.738	8	1.000
##	L2 =~							
##	Z4	1.000						
##	Z5	1.139	0.179	6.371	0.000	8.409	5	1.000
##	Z6	0.969	0.140	6.924	0.000	5.874	6	1.000
##	Z7	1.210	0.139	8.713	0.000	4.276	5	1.000
##	L3 =~							
##	Z8	1.000						
##	Z9	1.051	0.165	6.377	0.000	8.712	5	1.000
##	Z10	1.180	0.151	7.814	0.000	9.538	6	1.000
##	Z11	1.203	0.154	7.798	0.000	2.795	5	1.000
##								
##	L2 ~							
##	L1	1.261	0.426	2.962	0.003	0.503	1	1.000
##	L3 ~							
##	L1	1.123	0.312	3.598	0.000	0.801	3	1.000
##	L2	0.724	0.101	7.140	0.000			

PRIMARY INGREDIENTS

1. Specify Model
2. Transform Latent to Observed (L2O) variable model
3. Find Model Implied Instrumental Variables (MIIVs, pronounced to rhyme with "gives")
4. Estimate with Two Stage Least Squares (2SLS)
5. Test each overidentified equation

ROBUSTNESS

1. Distributional robustness

- Properties of MIV-2SLS are "distribution-free"
- Asymptotic, but do not assume normal error or observed variables
- Bootstrap option in MIVsem permits alternative way to estimate standard errors of parameter estimates

MIIVsem: Bootstrap SEs and CIs.

MIIVsem bootstrap standard errors

- Requested by setting `se = "boot"`
- Default number of replications is 1000
- Adjusted using the bootstrap argument (e.g. `bootstrap = 500`)

Reestimate the industrialization-democracy model with bootstrap standard errors

- Also set the `boot.ci` argument to `"perc"` which requests a confidence interval from the empirical 2.5th and 97.5th percentiles of the bootstrap sample.

```
miive(model.indem1, data, se = "boot", boot.ci = "perc")
```

MIIVsem: Bootstrap SEs and CIs.

Header information

- Shows bootstrap standard errors requested
- Lists number of replications requested
- Includes number of successful replications
- Documents confidence interval method

```
MIIVsem (0.5.2) results
```

Number of observations	75
Number of equations	10
Estimator	MIIV-2SLS
Standard Errors	bootstrap
Missing	listwise
Bootstrap reps requested	1000
Bootstrap reps successful	1000
Bootstrap intervals	Percentile

Note: Additional options for constructing bootstrap CIs are available. See the `boot.ci` argument of `miive` for more choices.

MIIVsem: Bootstrap SEs and CIs.

STRUCTURAL COEFFICIENTS:

	Estimate	Std.Err	Lower	Upper	Sargan	df	P(Chi)
L1 =~							
Z1	1.000						
Z2	2.078	0.127	1.787	2.300	8.301	8	0.405
Z3	1.751	0.132	1.461	1.972	8.738	8	0.365
L2 =~							
Z4	1.000						
Z5	1.139	0.134	0.850	1.373	8.409	5	0.135
Z6	0.969	0.137	0.696	1.237	5.874	6	0.437
Z7	1.210	0.122	0.950	1.434	4.276	5	0.510
L3 =~							
Z8	1.000						
Z9	1.051	0.142	0.711	1.303	8.712	5	0.121
Z10	1.180	0.148	0.858	1.452	9.538	6	0.146
Z11	1.203	0.148	0.891	1.484	2.795	5	0.731
L2 ~							
L1	1.261	0.422	0.406	2.059	0.503	1	0.478
L3 ~							
L1	1.123	0.297	0.524	1.745	0.801	3	0.849
L2	0.724	0.093	0.540	0.904			

EXERCISE: Bootstrap SEs and CIs.

Reestimate the political democracy example with bootstrap standard errors. Try setting the number of replications using bootstrap to a different number and compare the results to those obtained from 1000 bootstrap replications.

For example, below we request 500 bootstrap replications.

```
miive(model.indem1, data, se = "boot",  
      boot.ci = "perc", bootstrap = 500)
```


EXERCISE: Bootstrap SEs and CIs.

Below is code for combining estimates from four fitted models for easy comparison.

```
# Fit Models
fit.standard <- miive(model.indem1, data)
fit.boot.250 <- miive(model.indem1, data, se = "boot", bootstrap = 250)
fit.boot.500 <- miive(model.indem1, data, se = "boot", bootstrap = 500)
fit.boot.1000 <- miive(model.indem1, data, se = "boot", bootstrap = 1000)

# Save Estimates
est.standard <- estimatesTable(fit.standard)[, c("lhs", "op", "rhs", "se")]
est.boot.250 <- estimatesTable(fit.boot.250)[, c("lhs", "op", "rhs", "se")]
est.boot.500 <- estimatesTable(fit.boot.500)[, c("lhs", "op", "rhs", "se")]
est.boot.1000 <- estimatesTable(fit.boot.1000)[, c("lhs", "op", "rhs", "se")]

list.est <- list(est.standard, est.boot.250, est.boot.500, est.boot.1000)
compare.se <- Reduce(function(...) merge(..., by= c("lhs", "op", "rhs")), list.est)

colnames(compare.se) <- c("", "", "", "standard", "boot.250", "boot.500", "boot.1000")

compare.se
```

SOLUTION: Bootstrap SEs and CIs.

ROBUSTNESS

2. Structural misspecification robustness

- omitted paths
- omitted variables
- wrong number of dimensions

Bollen (2001): Suppose that for the j^{th} equation in the correctly specified model, the model implied IVs are in a matrix \mathbf{V}_j . The 2SLS estimator of the coefficients is robust for any misspecification in other equations under two conditions:

1. The equation being estimated is correctly specified
2. The misspecifications in the other equations do not alter the variables in \mathbf{V}_j

ROBUSTNESS

2. Structural misspecification robustness

- omitted paths
- omitted variables
- wrong number of dimensions

After demonstrating the use of lavaan's `simulateData()` function we'll explore the consequences of structural misspecifications on the MIIV-2SLS estimates.

First, we'll walk through one full example together.

ROBUSTNESS

Measurement Model Robustness to Latent Variable Model Misspecification

True Model :

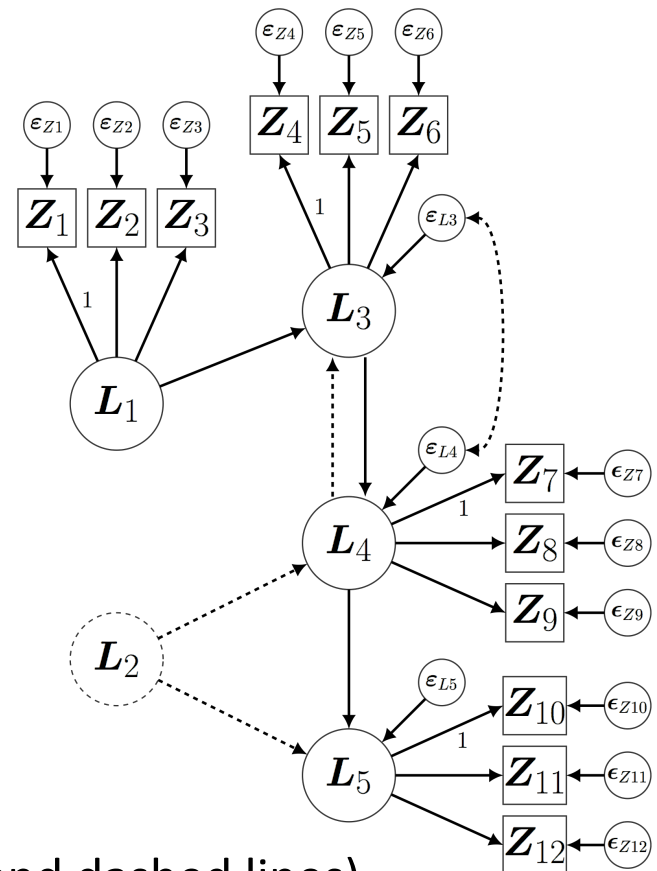
- Solid and dashed lines

Misspecifications

- Omitted paths, omitted latent variables
- Omitted covariances of errors

Simulation

- Simulated data to true model
- 1,000 observations
- 3 indicators per latent variable
- Estimate measurement model 2x
 1. Latent variable model is correct (solid and dashed lines)
 2. Latent variable model is incorrect (omitting dashed lines)



ROBUSTNESS

Use lavaan to simulate data

- `simulateData` function from lavaan.

Need to load lavaan

```
library("lavaan")
```

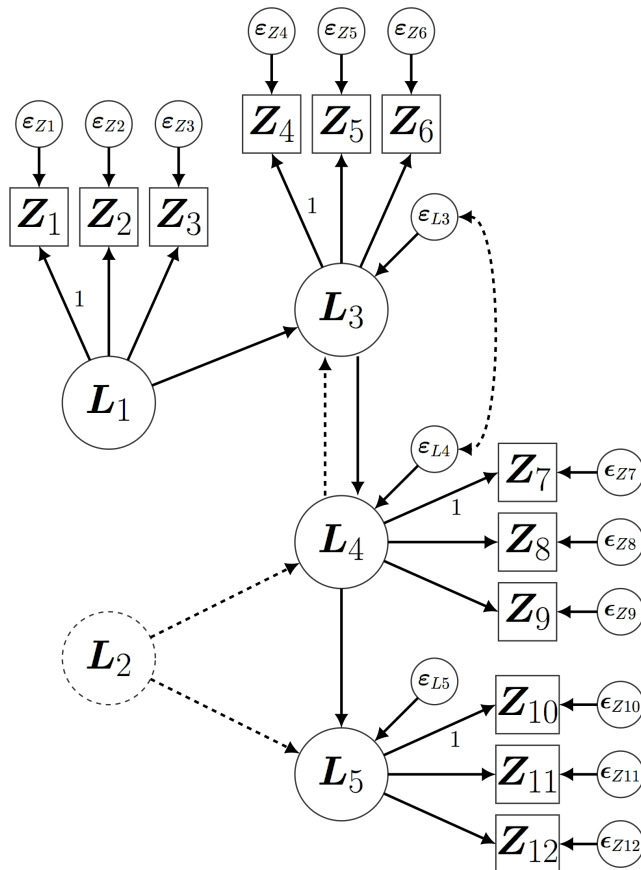
Specify the model from the previous slide

- Include population parameters
- Name this model: `model.sim.1`.

ROBUSTNESS

Here we specify the data generating model.

Note: Var(error) & Var(exogenous) =1 by default.



```
library("lavaan")
```

```
model.sim.1 <- '
```

```
  L1  =~ 1*Z1  + 1*Z2  + 1*Z3
```

```
  L2  =~ 1*Z4  + 1*Z5  + 1*Z6
```

```
  L3  =~ 1*Z7  + 1*Z8  + 1*Z9
```

```
  L4  =~ 1*Z10 + 1*Z11 + 1*Z12
```

```
  L5  =~ 1*Z13 + 1*Z14 + 1*Z15
```

```
  L3 ~ .3*L1 + .5*L4
```

```
  L4 ~ .5*L2 + .8*L3
```

```
  L5 ~ .3*L2 + .5*L4
```

```
  L3 ~~ .6*L4
```

```
,
```

ROBUSTNESS

Now use lavaan's simulateData function

- Set the model argument to model.sim.1
- Fix the number of observations to 1,000
- Choose random.seed of 123
 - Allows us to replicate our results exactly
- Save our dataset as data.sim.1

```
data.sim.1 <- simulateData(model = model.sim.1,  
                           sample.nobs = 1000,  
                           seed = 123)
```


ROBUSTNESS

Below we recap the commands used to simulate our data set.

```
library("lavaan")

model.sim.1 <- '
  L1  =~ 1*Z1  + 1*Z2  + 1*Z3
  L2  =~ 1*Z4  + 1*Z5  + 1*Z6
  L3  =~ 1*Z7  + 1*Z8  + 1*Z9
  L4  =~ 1*Z10 + 1*Z11 + 1*Z12
  L5  =~ 1*Z13 + 1*Z14 + 1*Z15

  L3 ~ .3*L1 + .5*L4
  L4 ~ .5*L2 + .8*L3
  L5 ~ .3*L2 + .5*L4

  L3 ~~ .2*L4
'

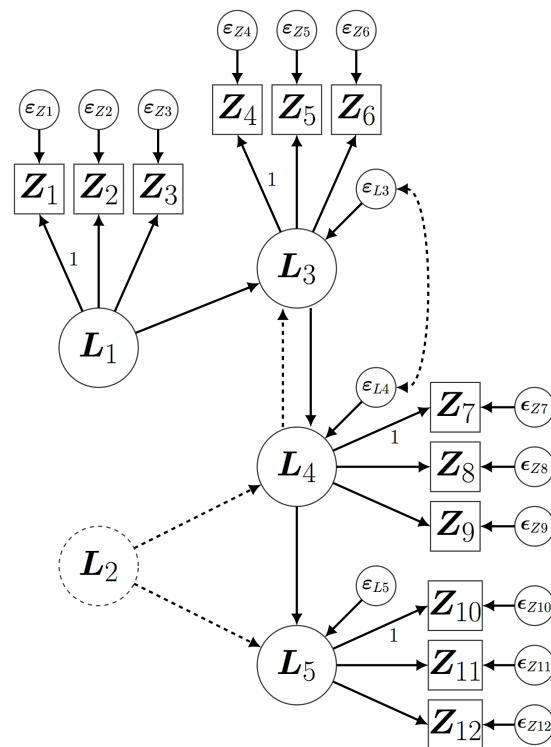
data.sim.1 <- simulateData(model = model.sim.1,
                           sample.nobs = 1000,
                           seed = 123)
```

Lastly, we need to define two estimating models:

1. `model.correct.1`
2. `model.misspecified.1`

`model.correct.1` corresponds to the correct model (both solid and dashed lines).

```
model.correct.1 <- '  
  
  L1  =~ Z1  + Z2  + Z3  
  L2  =~ Z4  + Z5  + Z6  
  L3  =~ Z7  + Z8  + Z9  
  L4  =~ Z10 + Z11 + Z12  
  L5  =~ Z13 + Z14 + Z15  
  
  L3 ~ L1 + L4  
  L4 ~ L2 + L3  
  L5 ~ L2 + L4  
  
  L3 ~~ L4  
  
'
```

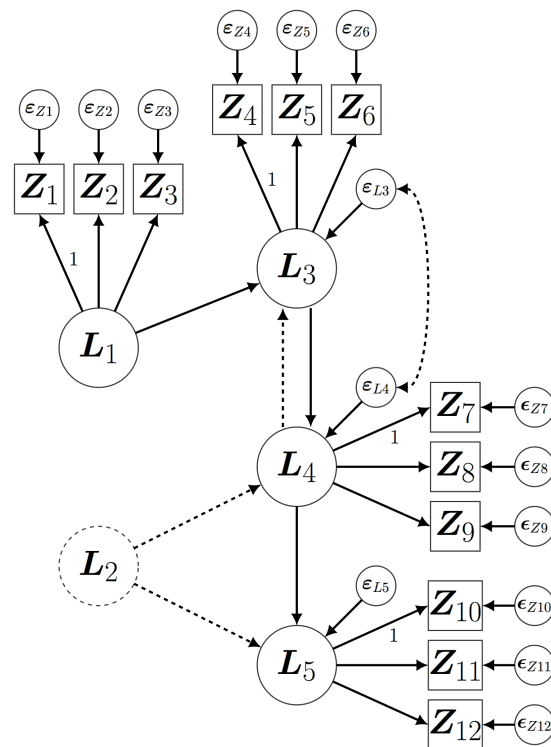


Lastly, we need to define two estimating models:

1. `model.correct.1`
2. `model.misspecified.1`

`model.misspecified.1` corresponds to the incorrect model (solid lines only).

```
model.misspecified.1 <- '  
  
  L1  =~ Z1  + Z2  + Z3  
  L2  =~ Z4  + Z5  + Z6  
  L3  =~ Z7  + Z8  + Z9  
  L4  =~ Z10 + Z11 + Z12  
  L5  =~ Z13 + Z14 + Z15  
  
  L3 ~ L1  
  L4 ~ L3  
  L5 ~ L4  
'
```



ROBUSTNESS

At this point we should have defined both the correct and misspecified models.

```
model.correct.1 <- '
```

```
  L1  =~ Z1  + Z2  + Z3  
  L2  =~ Z4  + Z5  + Z6  
  L3  =~ Z7  + Z8  + Z9  
  L4  =~ Z10 + Z11 + Z12  
  L5  =~ Z13 + Z14 + Z15
```

```
  L3 ~  L1 + L4  
  L4 ~  L2 + L3  
  L5 ~  L2 + L4
```

```
  L3 ~~ L4
```

```
'
```

```
model.misspecified.1 <- '
```

```
  L1  =~ Z1  + Z2  + Z3  
  L2  =~ Z4  + Z5  + Z6  
  L3  =~ Z7  + Z8  + Z9  
  L4  =~ Z10 + Z11 + Z12  
  L5  =~ Z13 + Z14 + Z15
```

```
  L3 ~  L1  
  L4 ~  L3  
  L5 ~  L4
```

```
'
```

ROBUSTNESS

Estimate correct & incorrect models in MIIVsem.

The `estimatesTable()` function

- Convenient way to store, view and manipulate the estimated parameters returned by `miive()`
- Save the fitted correct and misspecified models as `fit.cor.1`, and `fit.mis.1`, respectively.

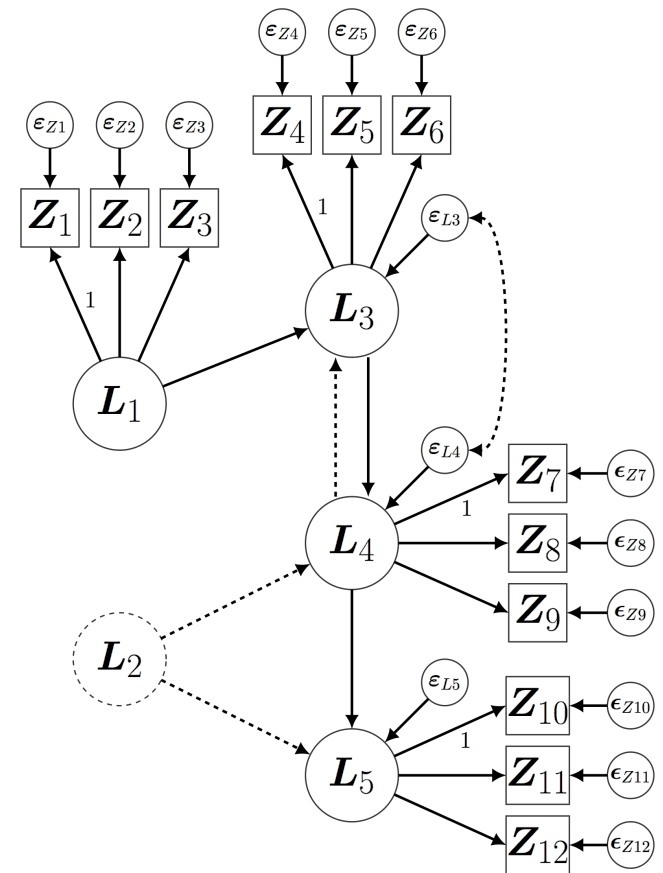
```
fit.cor.1 <- miive(model.correct.1, data.sim.1)
fit.mis.1 <- miive(model.misspecified.1, data.sim.1)

estimatesTable(fit.cor.1)
estimatesTable(fit.mis.1)
```

Simulation 1 Results

Measurement Model Robustness to Latent Variable Model Misspecification

##				est.cor.1	est.mis.1
##	1	L1 =~	Z1	1.0000000	1.0000000
##	2	L1 =~	Z2	1.0873919	1.0873919
##	3	L1 =~	Z3	1.0302098	1.0302098
##	4	L2 =~	Z4	1.0000000	1.0000000
##	5	L2 =~	Z5	1.0076301	1.0076301
##	6	L2 =~	Z6	0.9691372	0.9691372
##	7	L3 =~	Z7	1.0000000	1.0000000
##	8	L3 =~	Z8	0.9933688	0.9933688
##	9	L3 =~	Z9	0.9791256	0.9791256
##	10	L4 =~	Z10	1.0000000	1.0000000
##	11	L4 =~	Z11	1.0159817	1.0159817
##	12	L4 =~	Z12	1.0228551	1.0228551
##	13	L5 =~	Z13	1.0000000	1.0000000
##	14	L5 =~	Z14	1.0019276	1.0019276
##	15	L5 =~	Z15	0.9667204	0.9667204



EXERCISE: Simulation 2

Previously we examined the impact of a misspecified latent variable model on the measurement model estimates. We now consider another situation, the impact of a misspecified measurement model on the latent variable model estimates.

For this exercise you will:

1. Use lavaan's simulateData function to simulate 1,000 observations. In the data generating model set the regression coefficients and factor loadings to a value of 1, and the uniqueness covariances to a value of 0.3.
2. Fit the correct and misspecified models using MIIVsem.
3. Compare the estimates.

EXERCISE: Simulation 2

Latent Variable Model Robustness to Measurement Model Misspecification

True Model :

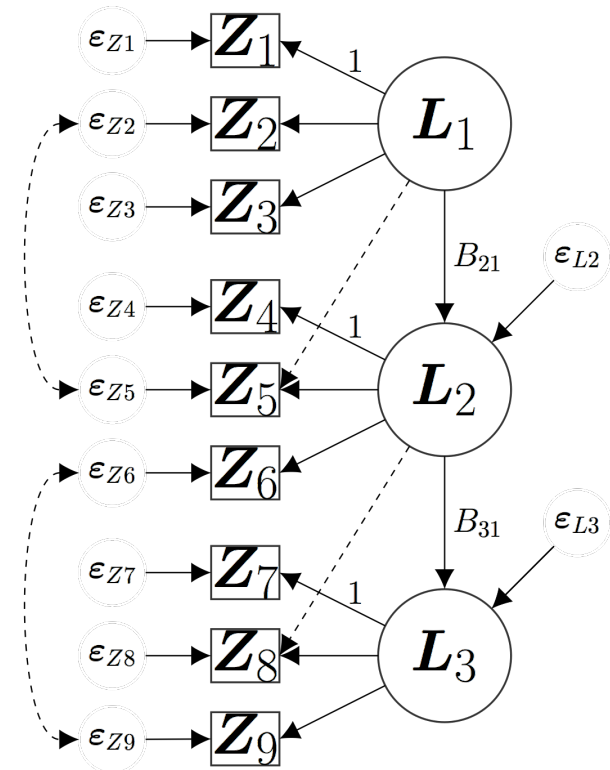
- Solid and dashed lines

Misspecifications

- Omitted correlated errors of indicators
- Omitted cross-loadings

Simulation

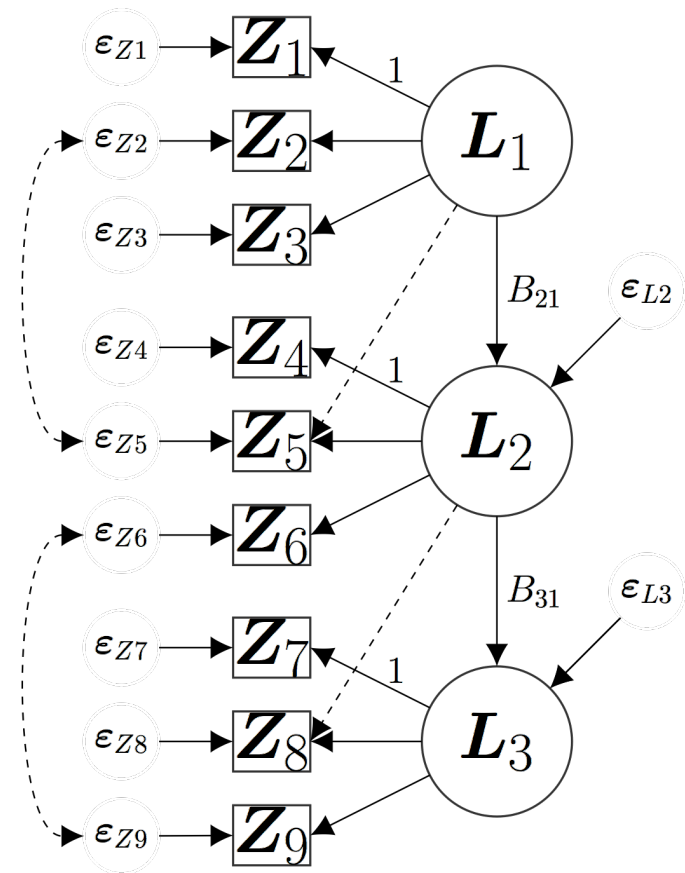
- Simulated data to true model
- 1,000 observations
- 3 indicators per latent variable
- Estimate latent variable model 2x
 1. Measurement model is correct (solid and dashed lines)
 2. Measurement model is incorrect (omitting dashed lines)



SOLUTION: Simulation 2

EXERCISE: Simulation 2

- Now that we have simulated the data we'll have to specify the models.
- The correct model includes the solid and dashed lines. The misspecified model contains the dashed lines only.



SOLUTION: Simulation 2

SOLUTION: Simulation 2

SOLUTION: Simulation 2

SOLUTION: Simulation 2

SOLUTION: Simulation 2

SOLUTION: Simulation 2

SOLUTION: Simulation 2

EXERCISE: Simulation 3

We now consider a final simulated data example. Here we make a different measurement model misspecification and ask you to answer the following three questions:

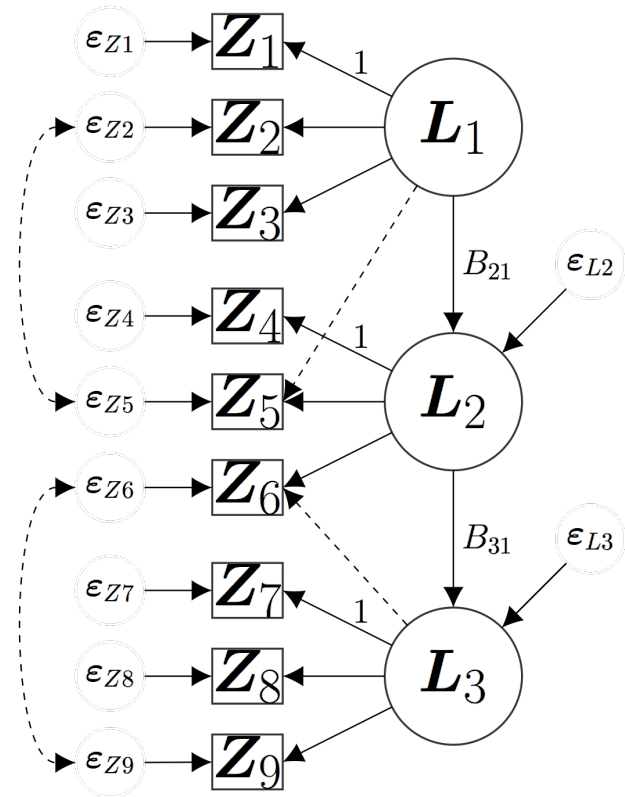
1. Do the robustness properties discussed earlier hold here?
2. If not, what is the reason for the change?
3. Is there any way of detecting this misspecification in practice?

Path diagram and questions presented on next slide.

EXERCISE: Simulation 3

Robustness Exercise

- Simulated 1,000 observations according to true model (solid and dashed lines).
- Estimate two models:
 1. Model 1: True model
 2. Model 2: Misspecified model where the dashed paths are omitted.



Questions

1. Do the robustness properties discussed earlier hold here?
2. If not, what is the reason for the change?
3. Is there any way of detecting this misspecification in practice?

SOLUTION: Simulation 3

SOLUTION: Simulation 3

ROBUSTNESS

2. Structural misspecification robustness

- MIIV-2SLS is robust because the MIIVs are the same for all models
- MIIV-2SLS depends on identification of equation, not identification of whole model
- MIIV-2SLS is NOT robust to all structural misspecifications
 - E.g., the measurement model estimates are not robust to the different models illustrated.

DIMENSIONALITY

In the next set of slides he show how MIIV-2SLS can be used to investigate dimensionality.

In doing so we demonstrate two features in MIIVsem:

1. How to add constraints to parameters in the lavaan style model syntax.
2. How to obtain Wald tests of these restrictions.

The data are included in MIIVsem (bollen1996) and come from a survey conducted in rural clusters of Tanzania to collect information on the perceived accessibility of a specific family planning facility that serviced each cluster (Bollen, 1996).

DIMENSIONALITY

Background Information:

Six informants were chosen from each cluster: 3 female and 3 male. New informants were chosen for each cluster. Each informant was independently asked to rate the accessibility of the facility. More specifically the women informants were asked to rate how women of childbearing age perceived the accessibility of the clinic and the men informants were asked to rate how accessible men perceived the clinic to be.

The female informants' ratings are `access1-3` and the male informants' ratings are `access4-6`.

DIMENSIONALITY

Model 1

We will begin by fitting a confirmatory factor analysis model with a single accessibility latent variable for male and female information.

Since the informants change from cluster to cluster, the ordering of the informants is arbitrary and we have no reason to believe the factor loadings would differ in a systematic way.

In Model 1 we will constrain all the factor loadings to equality.

DIMENSIONALITY

Equality Constraints and Parameter Restrictions

Identical to lavaan, labels can be used to specify equality constraints on parameters in the model syntax. Labels are prepended to the variable name using the `*` operator. For numeric constrains one can specify a number instead.

```
model.1 <- '  
    accessibility =~ 1*access1 + 1*access2 + 1*access3 +  
                    1*access4 + 1*access5 + 1*access6  
'
```

By constraining each loading to 1 we constrain all the loadings to equality.

DIMENSIONALITY

MIIVsem test statistics for constraints

- Large-sample Wald test of constraints imposed on coefficient matrix

F and χ^2 distributed test statistics asymptotically equivalent

- Performance may differ in small samples
- See Greene (2003, pp. 346-347) for details

Conduct Wald test by saving the miive object and using the `summary()` method request `restrict.tests=TRUE`

```
fit <- miive(model.1, bollen1996, sarg.adjust = "holm")  
  
summary(fit, restrict.tests = TRUE)
```

STRUCTURAL COEFFICIENTS:

	Estimate	Std.Err	z-value	P(> z)	Sargan	df	P(Chi)
accessibility =~							
access1	1.000						
access2	1.000				3.800	3	0.568
access3	1.000				1.107	3	0.775
access4	1.000				71.309	3	0.000
access5	1.000				82.893	3	0.000
access6	1.000				72.377	3	0.000

MIIV-2SLS LINEAR HYPOTHESIS TESTS:

access2_access1 = 1
access3_access1 = 1
access4_access1 = 1
access5_access1 = 1
access6_access1 = 1

Wald Test (Chi^2): 18.1306
Degrees of freedom: 5
Pr(>Chi^2) : 0.0028

Wald Test (F): 3.6261
Degrees of freedom: 5, 5
Pr(>F) : 0.0029

EXERCISE: Dimensionality 1

Model 2

The informants change from cluster to cluster but we have evidence the factor loadings for the female informants and those for the male informants are not equal. Fit a model where females have the same loading, and males loadings are also constrained equal. Note males loadings can differ from females. What has changed across the two model?

```
model.2 <- '
  accessibility =~ 1*access1 + 1*access2 + 1*access3 +
                  b*access4 + b*access5 + b*access6
  ,
miive(model.2, bollen1996, sarg.adjust = "holm")
```

SOLUTION: Dimensionality 1

EXERCISE: Dimensionality 2

Model 3

If women and men differ in their view of accessibility, then a two factor model could be more appropriate. Create a model that has Female Accessibility as the first factor and Male Accessibility as the second factor. Allow the two factors to correlate.

Scale the Female Accessibility latent variable to access1 and the Male Accessibility latent variable to access4. What happens to the overidentification tests?

SOLUTION: Dimensionality 2

CATEGORICAL ENDOGENOUS VARIABLES

Polychoric Instrumental Variable (PIV) Estimator

- Access indicators are ordinal
 - what happens if take account of ordinal nature?
- Polychoric correlations
 - assumes continuous underlying variable
 - ordinal variables are collapsed version
 - estimates of correlation between underlying variables
 - polychoric correlations then analyzed
- MIIVsem permits endogenous ordinal variables analyzed with polychoric correlations
 - Polychoric Instrumental Variable (PIV) estimator
 - See Bollen & Maydeu-Olivares (2007) for details

CATEGORICAL ENDOGENOUS VARIABLES

Following the convention used in lavaan, we use the ordered argument to indicate which variables in the model syntax are categorical. This will be demonstrated in the following example.

In our previous Accessibility example, responses were recorded on a 1-5 scale. We will reestimate our final two-factor model to demonstrate the PIV estimator.

CATEGORICAL ENDOGENOUS VARIABLES

Specify the model:

```
model <- '  
  femaleAccess =~ access1 + access2 + access3  
  maleAccess   =~ access4 + access5 + access6  
,
```

Declare the ordered categorical variables:

```
ordered <- c("access1", "access2", "access3",  
             "access4", "access5", "access6")
```

Fit the model:

```
miive(model, bollen1996, ordered = ordered)
```

MIIVsem (0.5.2) results

Number of observations	220
Number of equations	4
Estimator	MIIV-2SLS (PIV)
Standard Errors	standard
Missing	listwise

Parameter Estimates:

STRUCTURAL COEFFICIENTS:

	Estimate	Std.Err	z-value	P(> z)	Sargan	df	P(Chi)
Female =~							
access1	1.000						
access2	1.039	0.064	16.322	0.000			
access3	0.983	0.047	20.702	0.000			
Male =~							
access4	1.000						
access5	1.026	0.048	21.306	0.000			
access6	0.967	0.041	23.515	0.000			

Note: In the header, the estimator is now listed as MIIV-2SLS (PIV)

Reisenzein (1986)

The final example uses data from an experiment conducted by Reisenzein (1986).

The data are not publically available but we have been given permission to use it for this workshop.

As such, we will have to download the data.

Download Reizenzein (1986) Data

In R we can use the following code to save the Reizenzein data. The easiest way to get the data (across a number of platforms) is to install the readr package and run the following commands.

```
install.packages("readr")  
  
library(readr)  
  
address      <- "http://bit.ly/2qSfrQ5"  
reizenzein1986 <- read_csv(address)
```

Alternatively, you can download the CSV and read in directly from:
<https://raw.githubusercontent.com/zackfisher/M3/master/reizenzein1986.csv>

Reisenzein (1986)

Finally, using the path diagram below fit the models described by Reisenzein (1986). The first model contains solid lines only, the second contains both the solid and dashed lines.

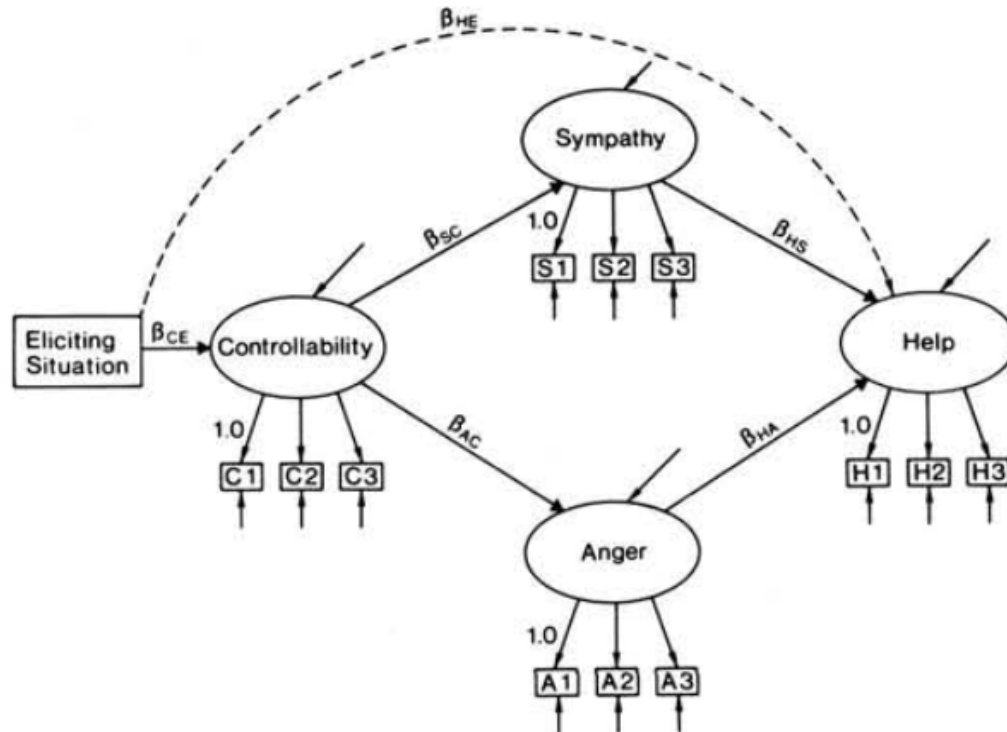


Figure 2 from Reisenzein (1986)

EXAMPLE: Reisenzein (1986)

Model 1 Syntax: Figure 2 without dashed line

```
model.reisenzein.1 <- '  
    sympathy =~ S1 + S2 + S3  
controllability =~ C1 + C2 + C3  
    anger =~ A1 + A2 + A3  
    help =~ H1 + H2 + H3  
  
    help ~ sympathy + anger  
    sympathy ~ controllability  
    anger ~ controllability  
controllability ~ E  
'
```


EXAMPLE: Reisenzein (1986)

Fit Model 1 using the MIIV-2SLS estimator:

```
miive(model.reisenzein.1, reisenzein1986)
```

SOLUTION: Reizenzein (1986)

SOLUTION: Reizenzein (1986)

SOLUTION: Reizenzein (1986)

SOLUTION: Reisenzein (1986)

Table 1 from Reisenzein (1986)

Controllability

- (C1) How controllable, do you think, is the cause of the person's present condition? (1 = *not at all under personal control*, 9 = *completely under personal control*)
- (C2) How responsible, do you think, is that person for his present condition? (1 = *not at all responsible*, 9 = *very much responsible*)
- (C3) I would think that it was the person's own fault that he is in the present situation. (1 = *no, not at all*, 9 = *yes, absolutely so*)

Sympathy

- (S1) How much sympathy would you feel for that person? (1 = *none at all*, 9 = *very much*)
- (S2) I would feel pity for this person. (1 = *none at all*, 9 = *very much*)
- (S3) How much concern would you feel for this person? (1 = *none at all*, 9 = *very much*)

Anger

- (A1) How angry would you feel at that person? (1 = *not at all*, 9 = *very much*)
- (A2) How irritated would you feel by that person? (1 = *not at all*, 9 = *very much*)
- (A3) I would feel aggravated by that person. (1 = *not at all*, 9 = *very much so*)

Table 1 from Reizenstein (1986)

Help

- (H1) How likely is it that you would help that person? (1 = *definitely would not help*, 9 = *definitely would help*)
- (H2) How certain would you feel that you would help the person? (1 = *not at all certain*, 9 = *absolutely certain*)
- (H3) Which of the following actions would you most likely engage in?
- 1 = *not help at all, try to stay uninvolved (subway)/I would not lend my notes at all (class notes);*
 - 2 = *try to alert other bystanders, but stay uninvolved myself (subway)/I would agree to lend the notes if the person is willing to xerox them immediately and give them back (class notes);*
 - 3 = *try to inform the conductor or another official in charge (subway)/I would agree to lend the notes if the person promises to give them back the following day (class notes);*
 - 4 = *go over and help the person to a seat (subway)/I would lend him the notes without any special conditions (class notes);*
 - 5 = *help in any way that might be necessary, including if necessary first aid and/or accompanying the person to a hospital (subway only).*

Table 3 from Reisenzein (1986)

Model	$\chi^2 (N = 138)$	<i>df</i>	<i>p</i>
Null model	1,463.94	78	<.001
Model 1	86.58	61	<.020
Model 2 (with β_{HC} added)	85.95	60	<.016
Model 3 (with a correlation between the error terms of sympathy and anger added)	85.44	60	<.018
Model 4 (with both β_{HC} and the correlation between the errors of sympathy and anger added)	84.97	59	<.016
Model 5 (with β_{HE} added)	82.25	60	<.029
Model 5' (= 5 with 2 correlated error terms)	67.28	58	$\cong .189$
Model comparisons			
1 versus 2	0.63	1	.50 > <i>p</i> > .25
1 versus 3	1.14	1	.50 > <i>p</i> > .25
1 versus 4	1.61	2	.50 > <i>p</i> > .25
1 versus 5	4.33	1	<.05
1 versus null	1,377.36	17	<.001
5 versus null	1.69	18	<.001
5 versus 5'	14.97	2	<.001

SOLUTION: Reizenzein (1986)

SOLUTION: Reizenzein (1986)

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SOLUTION: Reizenzein (1986)

SOLUTION: Reizenzein (1986)

EXTENSIONS

- Categorical endogenous variables
 - Bollen & Maydeu-Oliveres (2007)
 - Nestler (2012)
 - Jin, Luo, & Yang-Wallentin (2016)
- Interactions of latent variables
 - Bollen (1995)
 - Bollen & Paxton (1998)
- 2nd Order growth curve models
 - Nestler (2014)

EXTENSIONS

- Higher order factor analysis
 - Bollen & Biesanz (2002)
- Specification error tests for nonlinearity and interactions
 - Nestler (2015)
- Testing dimensionality of measures
 - Bollen (2011)
- General Method of Moments estimator
 - Bollen, Kolenikov, & Bauldry (2014)

Resources

lavaan Resources:

- <http://lavaan.ugent.be/>

MIIVsem Github

- <https://github.com/zackfisher/MIIVsem>
- readme file with examples
- vignette coming soon

MIIVsem Planned Developments

- Missing data (normal or nonnormal distributions)
- General Method of Moments estimator
 - Permits subsets of equations to estimate
- Additional diagnostic tests of MIIVs
- Weak MIIV diagnostics
- MIIV selection methods (e.g. LASSO)

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