

# Structural Equation Models Using Stata

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## 1 Introduction

### 1.1 Goals

#### Goals

- Learn a bit about structural equation modeling (SEM) and generalized structural equation modeling (GSEM)
- Learn about Stata’s facilities for fitting SEM and GSEM

---

### 1.2 Stata Background

#### Stata’s Tenets

- “Stata” rhymes with “data”
- Type a little, get a little
  - ◊ Click a little, get a little works fine, also
- Simple reproducibility

- Easy and complete extensibility
  - Easy sharing
- 

## Notes and Slides

- Every slide in the presentations is in the notes
  - The output from commands is only in the notes
- 

## Typography

- For commands, there are various fonts which can be used
    - ◇ Items which must be typed as shown will be in a monospaced font
    - ◇ *Items for which a substitution is needed* will be in *italics*
    - ◇ [ *Optional items* ] will be [ *in square brackets* ], though the brackets do not get typed
  - Example Stata commands will often be preceded by a .
    - ◇ The . is a prompt and does not get typed—it is for distinguishing input from output in the notes. In the handouts, the commands are both boldfaced and slanted. This is done so that they are easier to see on the page (even though it conflicts with the above rules).
- 

## 1.3 What is SEM?

### Descriptions of Linear SEM

- SEM is a class of statistical techniques that allows us to test hypotheses about relationships among variables
  - SEM may also be referred to as Analysis of Covariance Structures
    - ◇ SEM fits models using the observed covariances and, possibly, means
  - SEM encompasses other statistical methods such as correlation, linear regression, and factor analysis
- 

### Descriptions of Linear SEM (Continued)

- SEM is a multivariate technique that allows us to estimate a system of equations
    - ◇ Variables in these equations may be measured with error
    - ◇ There may be variables in the model that cannot be measured directly
- 

### SEM in Stata

- The `sem` command is used to fit standard linear SEM models
  - The `gsem` command is used to fit generalizations of linear SEM
    - ◇ Generalized linear models including continuous, binary, ordinal, nominal, count, and survival outcomes
    - ◇ Multilevel models including random intercepts, random slopes, and crossed effects
  - Both types of models can be specified using either commands or path diagrams via the SEM Builder
-

## Types of Variables

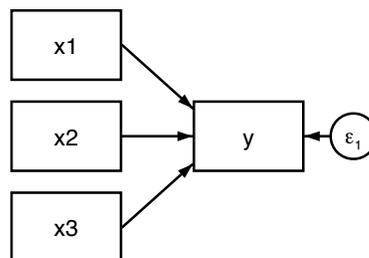
- Observed variables (manifest variables)
    - ◇ We have observed values of these variables in our dataset
    - ◇ Or we have variances, covariances, and possibly means based on observed values
  - Latent variables (unobserved variables, factors)
    - ◇ May represent the following
      - ★ Hypothetical constructs
      - ★ Variables that cannot be directly measured
      - ★ True values of variables measured with error
      - ★ Unobserved heterogeneity
      - ★ Errors or disturbances
    - ◇ Latent variables are measured by observed variables known as measurements or indicators
- 

## Types of Variables (Continued)

- Endogenous variables
    - ◇ Also known as  $y$ , dependent, or response variables
    - ◇ Predicted by one or more other variables
    - ◇ May predict other endogenous variables
  - Exogenous variables
    - ◇ Also known as  $x$ , independent, or explanatory variables
    - ◇ Variables that are not predicted by any other variables in the model
    - ◇ May be correlated with other variables in the model
- 

## Path Diagrams

- Observed variables are represented by rectangles
- Latent variables are represented by ovals or circles
- Paths are represented by arrows
- Covariances are represented by curved lines with arrows at each end
- The path diagram below corresponds to a linear regression of  $y$  on  $x_1$ ,  $x_2$ , and  $x_3$



## 2 Linear SEM

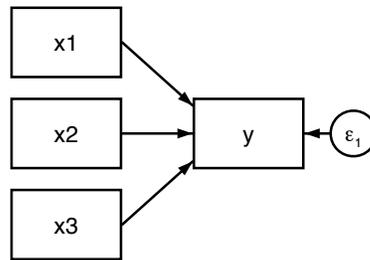
### 2.1 Introduction

#### Data

- `sem` allows two types of data
  - Datasets with individual observations
  - Datasets made up of summary statistics, specifically covariance or correlation matrices; and possibly means
    - ◇ See `help ssd` for more information about working with summary statistics data
- 

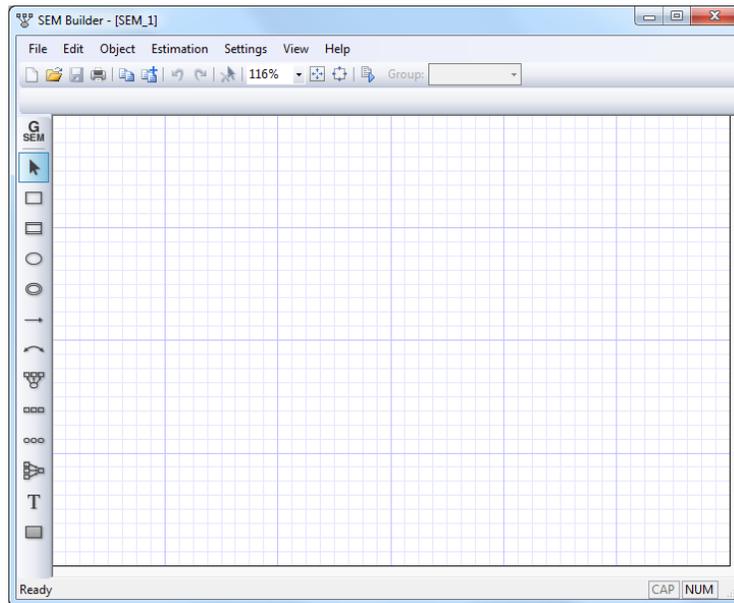
#### Basic Syntax

- `sem paths [if] [in] [weight] [, options]`
- The basic rules are
  - ◇ All paths are placed inside parentheses
  - ◇ Arrows point towards dependent variables
- Beyond that the *paths* specifications are flexible
- The three commands below all fit the path model shown here
  - . `sem (y <- x1 x2 x3)`
  - . `sem (x1 x2 x3 -> y)`
  - . `sem (x1 -> y) (x2 -> y) (x3 -> y)`



#### The SEM Builder

- To open the SEM Builder, type `sembuilder` or click on **Statistics > SEM (structural equation modeling) > Model building and estimation**



- The tools along the left-hand side allow us to draw the path diagram
  - Use the menus at the top to customize the appearance of the path diagram, fit the model, customize the appearance of the results, and more
- 

## 2.2 Path Models

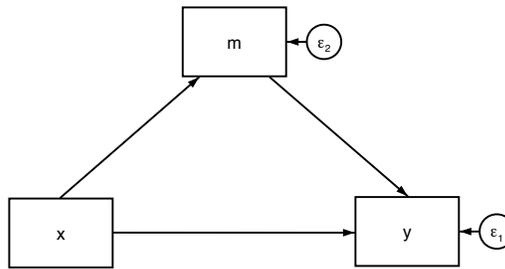
### Path Analysis

- We will begin by looking at some examples of path analysis
  - Path models include only observed variables and their error terms
  - These models can be simple or they may include many observed variables with intricate relationships
- 

### Mediation Models

- In a mediation model, a variable  $x$  is hypothesized to predict  $y$  in two ways
    - ◇ Directly
    - ◇ Indirectly because  $x$  predicts a third variable  $m$  which in turn predicts  $y$
  - Using `sem` we can fit all of the equations in the mediation model simultaneously
- 

### A Simple Mediation Model



- The command for the above model is

```
. sem (m <- x) (y <- x m)
```

### Job Satisfaction Data

- Fogarty et al. (1999) fit a variety of models that examine relationships among positive and negative affectivity, stress, coping, strain, and job satisfaction
  - ◊ We'll fit a much simpler model
- The data for this example are stored as summary statistics in `jobsat.dta`

```
. use jobsat
```

(Data from Fogarty et al. (1999))

- We can learn about the variables

```
. ssd describe
```

```
Summary statistics data from jobsat.dta
  obs:           114           Data from Fogarty et al. (1999)
  vars:           6           16 Sep 2015 19:24
-----
variable name      variable label
-----
stress             sum of environmental state items
coping             sum of resources for dealing with stre..
strain             sum of personal reaction to stress items
na                 sum of negative affectivity items (neg..
pa                 sum of positive affectivity items (pos..
satisfaction       sum of job satisfaction items
-----
```

- We can also look at their summary statistics

```
. ssd list
```

```
Observations = 114
```

```
Means:
```

```

      stress      coping      strain      na      pa      satisfaction
      136.11      127.72      80.91      18.57      35.4      60.81

```

```

Standard deviations:
      stress      coping      strain      na      pa      satisfaction
      22.48      18.13      19.65      7      6.22      10.84

Correlations:
      stress      coping      strain      na      pa      satisfaction
      1
      -.38      1
      .59      -.58      1
      .26      -.42      .58      1
      -.29      .49      -.46      -.28      1
      -.46      .27      -.51      -.21      .42      1

```

## Fitting a Mediation Model

- As an example, we can fit a model where strain mediates the effect of negative affectivity on job satisfaction

```
. sem (satisfaction <- strain na) (strain <- na)
```

Endogenous variables

Observed: satisfaction strain

Exogenous variables

Observed: na

Fitting target model:

Iteration 0: log likelihood = -1275.3885

Iteration 1: log likelihood = -1275.3885

```

Structural equation model          Number of obs   =       114
Estimation method = ml
Log likelihood = -1275.3885

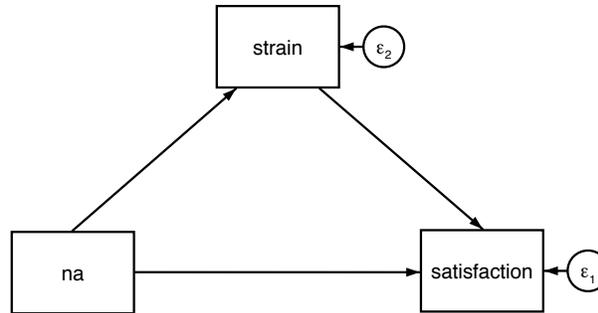
```

```

-----
              |          OIM
              |          Coef.  Std. Err.   z    P>|z|    [95% Conf. Interval]
-----+-----
Structural    |
satisfaction  |
      strain |  -.3227126   .0541461   -5.96  0.000   -.428837   -.2165882
      na     |   .2002222   .1519959    1.32  0.188   -.0976842   .4981286
      _cons  |   83.20255   3.68243   22.59  0.000   75.98512   90.41998
-----+-----
strain        |
      na     |   1.628143   .2141733    7.60  0.000    1.208371    2.047915
      _cons  |   50.67539   4.248061   11.93  0.000   42.34934   59.00143
-----+-----
var(e.satisfaction) |  84.88763   11.24364                65.47869   110.0497
var(e.strain)      |  253.9833   33.6409                195.9118   329.268
-----
LR test of model vs. saturated: chi2(0) =      0.00, Prob > chi2 =      .

```

- In path diagram form the model is



### Direct, Indirect, and Total Effects

- Direct effects are the coefficient estimates we see in the output
  - ◊ The direct effect of `na` on `satisfaction` is `.2`
- We can calculate the indirect effect of negative affectivity on job satisfaction by multiplying the appropriate coefficients
  - ◊ The path coefficient from `na` to `strain` is roughly `1.62`
  - ◊ The path coefficient from `strain` to `satisfaction` is roughly `-.322`
  - ◊  $1.62 \times -.322 = -.522$  so the indirect effect is roughly `-.52`
- The total effect is the sum of the direct and indirect effects
  - ◊ The total effect of negative affectivity on job satisfaction is  $.2 + (-.52) = -.32$

### `estat teffects`

- We can obtain direct, indirect, and total effects and their standard errors using `estat teffects`

```
. estat teffects
```

```
Direct effects
```

	Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
-----						
Structural						
satisfaction						
strain	-.3227126	.0541461	-5.96	0.000	-.428837	-.2165882
na	.2002222	.1519959	1.32	0.188	-.0976842	.4981286
-----						
strain						
na	1.628143	.2141733	7.60	0.000	1.208371	2.047915
-----						

```
Indirect effects
```

		OIM		z	P> z	[95% Conf. Interval]	
		Coef.	Std. Err.				
Structural							
satisfaction							
	strain	0	(no path)				
	na	-.5254222	.1120216	-4.69	0.000	-.7449805	-.3058639
strain							
	na	0	(no path)				

Total effects

		OIM		z	P> z	[95% Conf. Interval]	
		Coef.	Std. Err.				
Structural							
satisfaction							
	strain	-.3227126	.0541461	-5.96	0.000	-.428837	-.2165882
	na	-.3252	.1418029	-2.29	0.022	-.6031285	-.0472715
strain							
	na	1.628143	.2141733	7.60	0.000	1.208371	2.047915

- What do we see?
  - ◇ The direct effect of na on satisfaction is not significantly different from 0
  - ◇ The direct effect of strain on satisfaction is significant different from 0
  - ◇ The indirect effect of na on satisfaction is also significantly different from 0
  - ◇ The direct effect of na on satisfaction can be said to be fully mediated by strain

Standardized coefficients

- We can replay the model with standardized coefficients using

`. sem, standardized`

```
Structural equation model           Number of obs   =       114
Estimation method   = ml
Log likelihood      = -1275.3885
```

		OIM		z	P> z	[95% Conf. Interval]	
Standardized		Coef.	Std. Err.				
Structural							
satisfaction							
	strain	-.584991	.0857388	-6.82	0.000	-.753036	-.4169459
	na	.1292948	.0974336	1.33	0.185	-.0616716	.3202611
	_cons	7.709399	.4148133	18.59	0.000	6.89638	8.522419
strain							
	na	.58	.0566844	10.23	0.000	.4689007	.6910993
	_cons	2.590286	.3461981	7.48	0.000	1.91175	3.268822

```

var(e.satisfaction)| .7288065 .0709659 .602183 .8820557
var(e.strain)| .6636 .0657539 .5464667 .8058404

```

```

-----
LR test of model vs. saturated: chi2(0) = 0.00, Prob > chi2 = .

```

- We expect that a one standard deviation increase in strain would produce a .58 standard deviation decrease in satisfaction, holding negative affectivity constant
- We can also obtain standardized indirect and total effects

```

. estat teffects, standardized nodirect

```

```

Indirect effects

```

```

-----
                |          OIM
                |      Coef.  Std. Err.    z    P>|z|          Std. Coef.
-----+-----
Structural      |
satisfaction    |
  strain        |          0 (no path)                0
  na            |  -.5254222  .1120216   -4.69  0.000        -.3392948
-----+-----
strain          |
  na            |          0 (no path)                0
-----

```

```

Total effects

```

```

-----
                |          OIM
                |      Coef.  Std. Err.    z    P>|z|          Std. Coef.
-----+-----
Structural      |
satisfaction    |
  strain        |  -.3227126  .0541461   -5.96  0.000        -.584991
  na            |  -.3252     .1418029   -2.29  0.022        -.21
-----+-----
strain          |
  na            |  1.628143   .2141733    7.60  0.000         .58
-----

```

◇ The standardized indirect effects are the products of standardized coefficients

### Equation Level Goodness-of-fit

- We can also obtain variance decomposition and R-squared for each of the endogenous variables in the model

```

. estat eqgof

```

```

Equation-level goodness of fit

```

```

-----
                |          Variance
                |      fitted predicted  residual | R-squared    mc    mc2
-----+-----
observed        |
satisfaction    |  116.4748  31.58722  84.88763 | .2711935  .5207624  .2711935
  strain        |  382.7355  128.7522  253.9833 | .3364     .58     .3364
-----+-----
overall         |          | .3463495
-----

```

```
mc = correlation between depvar and its prediction
mc2 = mc^2 is the Bentler-Raykov squared multiple correlation coefficient
```

- About 27% of variation in satisfaction is explained by the model
- To obtain a Wald test for the null hypothesis that all coefficients in an equation are 0 we can use

```
. estat eqtest
```

```
Wald tests for equations
-----+-----
                |      chi2   df      p
-----+-----
observed        |
satisfaction    |      42.42   2      0.0000
  strain       |      57.79   1      0.0000
-----+-----
```

---

## Nonrecursive Path Models

- The examples so far have been of recursive models
- Models that contain feedback loops or correlated error terms are said to be nonrecursive
- `sem` can be used to fit nonrecursive models
- Checking whether a nonrecursive model is identified can be simple or complex, depending on the model
- Stata provides tools for evaluating identification of nonrecursive models, for more information see `help estat stable`

---

## 2.3 Models with Latent Variables

### Models with Latent Variables

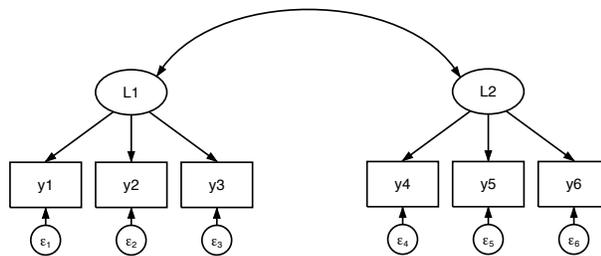
- Models with latent variables can estimate and accommodate measurement error
- Some variables cannot be directly measured without error
  - ◊ But we may be able to collect multiple measurements each of which contains some error
- Confirmatory factor analysis (CFA) allows us to evaluate how well the items we collect measure the corresponding concept
- CFA models are also called measurement models
- Examples: Personality features, depression, attitudes

## Confirmatory Factor Analysis

- In a confirmatory factor analysis (CFA) model, one or more latent variables is measured by a series of observed variables
    - ◊ The latent variables may be correlated, but no structural paths are specified
  - Each latent variable is associated with a set of observed variables
  - These models are confirmatory in the sense that we specify them based on prior knowledge or theory about
    - ◊ What the latent variables represent
    - ◊ Which observed variables are associated with each latent variable
  - This is unlike exploratory factor analysis where all observed variables are allowed to measure each of the latent variables
- 

## Confirmatory Factor Analysis (continued)

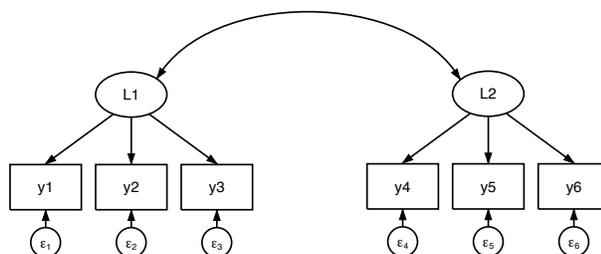
- At least 3 measurement variables are required to identify a model that contains only a single latent variable
- Sometimes also called a measurement model
- Here is an example of a path diagram for a CFA model



## Syntax for a CFA Model

- By default, variables with names beginning with a capital letter are assumed to be latent variables
- Three equivalent methods of fitting the CFA model shown below are

```
. sem (L1 -> y1 y2 y3) (L2 -> y4 y5 y6)
. sem (y1 y2 y3 <- L1) (y4 y5 y6 <- L2)
. sem (L1 -> y1) (L1 -> y2) (L1 -> y3) ///
.      (L2 -> y4) (L2 -> y5) (L2 -> y6)
```



## Education Data

- Holzinger and Swineford (1939) measured the abilities of students across a variety of areas
- Five of the observed variables measure verbal skills
- Let's open the data and take a look at these variables

```
. use hsdata  
. codebook general paragraph sentence wordc wordm
```

(Data from Holzinger and Swineford (1939))

```
-----  
generalgeneral information  
-----
```

```
      type: numeric (float)  
  
      range: [8,84]           units: 1  
unique values: 57           missing .: 0/301  
  
      mean: 40.5914  
      std. dev: 12.3807  
  
percentiles:      10%      25%      50%      75%      90%  
                  24       31       41       49       56
```

```
-----  
paragraphparagraph comprehension  
-----
```

```
      type: numeric (float)  
  
      range: [0,19]          units: 1  
unique values: 20          missing .: 0/301  
  
      mean: 9.18272  
      std. dev: 3.49235  
  
percentiles:      10%      25%      50%      75%      90%  
                  5        7        9        11       14
```

```
-----  
sentencesentence completion  
-----
```

```
      type: numeric (float)  
  
      range: [4,28]         units: 1  
unique values: 25          missing .: 0/301  
  
      mean: 17.3621  
      std. dev: 5.16189  
  
percentiles:      10%      25%      50%      75%      90%  
                  10       14       18       21       24
```

```
-----  
wordcword classification  
-----
```

```

type: numeric (float)

range: [10,43]          units: 1
unique values: 31      missing .: 0/301

mean: 26.1262
std. dev: 5.67544

percentiles:    10%    25%    50%    75%    90%
                19     23     26     30     33

```

```
-----
wordm                                                    word meaning
-----
```

```

type: numeric (float)

range: [1,43]          units: 1
unique values: 40      missing .: 0/301

mean: 15.299
std. dev: 7.66922

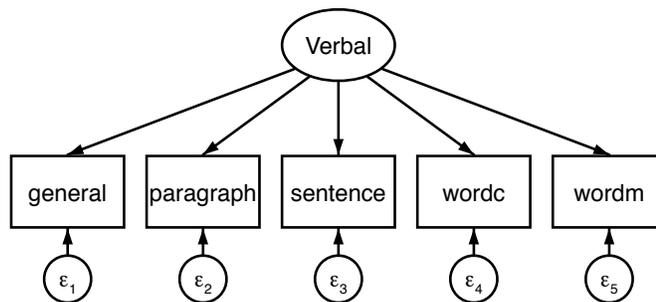
percentiles:    10%    25%    50%    75%    90%
                7     10     14     19     26

```

- We'll use the observed variables `general`, `paragraph`, `sentence`, `wordc`, and `wordm` as indicators for the latent variable representing verbal abilities

### Fitting a Single Factor CFA

- The latent variable, Verbal, is assumed to cause the observed variables



- The `sem` command to fit the model is

```

. sem (Verbal -> general paragraph sentence wordc wordm)

```

Endogenous variables

Measurement: `general paragraph sentence wordc wordm`

Exogenous variables



- ◇ If the model includes means, the respective mean vectors are included in this test

## Examining Model Fit

- We can examine the fit of this model using

```
. estat gof, stats(all)
```

```
-----
```

Fit statistic	Value	Description
-----		
Likelihood ratio		
chi2_ms(5)	18.739	model vs. saturated
p > chi2	0.002	
chi2_bs(10)	1005.075	baseline vs. saturated
p > chi2	0.000	
-----		
Population error		
RMSEA	0.096	Root mean squared error of approximation
90% CI, lower bound	0.052	
upper bound	0.144	
pclose	0.043	Probability RMSEA <= 0.05
-----		
Information criteria		
AIC	8836.854	Akaike's information criterion
BIC	8892.460	Bayesian information criterion
-----		
Baseline comparison		
CFI	0.986	Comparative fit index
TLI	0.972	Tucker-Lewis index
-----		
Size of residuals		
SRMR	0.020	Standardized root mean squared residual
CD	0.918	Coefficient of determination
-----		

- The first  $\chi^2$  test is the same test reported in the output from `sem`
- The second  $\chi^2$  compares the saturated model with a baseline model that includes
  - ◇ The means and variances of all observed variables, and
  - ◇ The covariances of all observed exogenous variables
  - ◇ Different authors define the baseline model differently

## More Model Fit

- A variety of measures of fit have been proposed for SEM
  - ◇ For many of these measures a variety of standards for what constitutes good or acceptable fit have also been proposed
- `sem` provides the following
  - ◇ RMSEA or root mean square error of approximation
    - ★ The  $p$ -value labeled `pclose` corresponds to a test of  $RMSEA < .05$
  - ◇ AIC and BIC

- ◇ The comparative fit index (CFI) and Tucker-Lewis index (TLI)
- ◇ Standardized root mean squared residual (SRMR)
- ◇ Coefficient of determination (CD)

## Standardized Coefficients

- We can replay the model to obtain standardized coefficients

```
. sem, standardized

Structural equation model                Number of obs   =       301
Estimation method   = ml
Log likelihood      = -4403.4268

( 1) [general]Verbal = 1
```

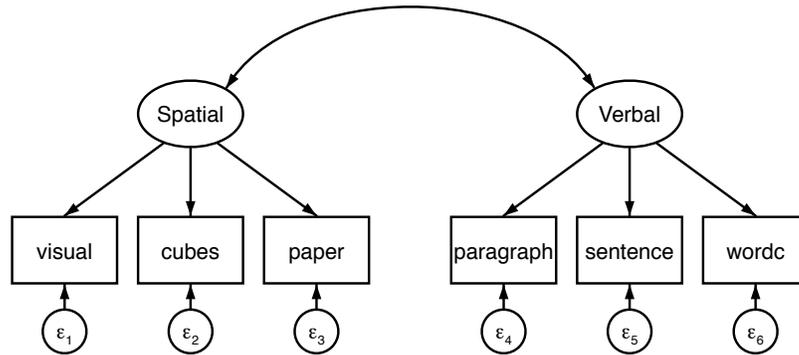
	Standardized	Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
-----							
Measurement							
general							
Verbal		.8376031	.0209013	40.07	0.000	.7966373	.8785688
_cons		3.284052	.145731	22.54	0.000	2.998424	3.56968
-----							
paragraph							
Verbal		.8177789	.0224446	36.44	0.000	.7737883	.8617694
_cons		2.633762	.1218401	21.62	0.000	2.39496	2.872564
-----							
sentence							
Verbal		.8738473	.017864	48.92	0.000	.8388345	.90886
_cons		3.369123	.1489219	22.62	0.000	3.077242	3.661005
-----							
wordc							
Verbal		.736878	.0293638	25.09	0.000	.679326	.7944299
_cons		4.611049	.1965727	23.46	0.000	4.225773	4.996324
-----							
wordm							
Verbal		.8435557	.02038	41.39	0.000	.8036117	.8834998
_cons		1.998179	.0997732	20.03	0.000	1.802627	2.193731
-----							
var(e.general)		.2984211	.035014			.2371141	.3755793
var(e.paragraph)		.3312377	.0367094			.2665665	.4115988
var(e.sentence)		.236391	.0312208			.1824779	.3062326
var(e.wordc)		.4570109	.043275			.379599	.5502094
var(e.wordm)		.2884137	.0343833			.2283178	.3643277
var(Verbal)		1	.			.	.
-----							

```
LR test of model vs. saturated: chi2(5)   =    18.74, Prob > chi2 = 0.0021
```

- The standardized loading is the correlation between the latent variable and the observed variable when each indicator measures only a single latent variable
- The standardized error variances are the proportion of variation not explained by the latent variable

## Two Factor CFA

- Now we'll add a second latent variable called *Spatial* which represents students' spacial abilities, using the indicators *visual*, *cube*, and *paper*



- Read nothing into the fact that we have reduced the number of items for the variable *Verbal* from five to three

## Fitting a Two Factor CFA

- We can fit this model using

```
. sem (Spatial -> visual cubes paper) ///
      (Verbal -> paragraph sentence wordc)
```

Endogenous variables

Measurement: visual cubes paper paragraph sentence wordc

Exogenous variables

Latent: Spatial Verbal

Fitting target model:

```
Iteration 0: log likelihood = -5046.1909
Iteration 1: log likelihood = -5046.0419
Iteration 2: log likelihood = -5046.0415
```

```
Structural equation model          Number of obs   =       301
Estimation method   = ml
Log likelihood      = -5046.0415
```

```
( 1) [visual]Spatial = 1
( 2) [paragraph]Verbal = 1
```

		OIM				
		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Measurement						
	visual					
	Spatial	1 (constrained)				
	_cons	29.61462	.4030662	73.47	0.000	28.82462 30.40461

```

cubes      |
      Spatial |      .364576      .0793793      4.59      0.000      .2089954      .5201566
      _cons |      24.35216      .2710169      89.85      0.000      23.82098      24.88334
-----+-----
paper      |
      Spatial |      .2662524      .0525865      5.06      0.000      .1631847      .3693201
      _cons |      14.22924      .1628644      87.37      0.000      13.91003      14.54844
-----+-----
paragraph  |
      Verbal |              1 (constrained)
      _cons |      9.182724      .2009609      45.69      0.000      8.788848      9.5766
-----+-----
sentence   |
      Verbal |      1.618814      .1038495      15.59      0.000      1.415273      1.822355
      _cons |      17.36213      .2970316      58.45      0.000      16.77995      17.9443
-----+-----
wordc      |
      Verbal |      1.484747      .1104262      13.45      0.000      1.268316      1.701179
      _cons |      26.12625      .3265833      80.00      0.000      25.48615      26.76634
-----+-----
var(e.visual)|      21.41672      5.034175              13.51049      33.94961
var(e.cubes)|      18.45538      1.700839              15.40553      22.10901
var(e.paper)|      6.035589      .6176517              4.938693      7.376109
var(e.paragraph)|      4.064789      .4958005              3.200465      5.162533
var(e.sentence)|      5.353155      1.049893              3.644744      7.862355
var(e.wordc)|      14.26686      1.429614              11.72286      17.36294
var(Spatial)|      27.48446      5.927568              18.00979      41.9436
var(Verbal)|      8.091177      1.004038              6.344329      10.319
-----+-----
cov(Spatial,Verbal)|      7.390188      1.374653      5.38      0.000      4.695917      10.08446
-----+-----
LR test of model vs. saturated: chi2(8) = 15.45, Prob > chi2 = 0.0509

```

- We can examine model fit using

```
. estat gof, stats(all)
```

```

-----+-----
Fit statistic      |      Value      Description
-----+-----
Likelihood ratio   |
      chi2_ms(8) |      15.454      model vs. saturated
      p > chi2 |      0.051
      chi2_bs(15) |      559.669      baseline vs. saturated
      p > chi2 |      0.000
-----+-----
Population error   |
      RMSEA |      0.056      Root mean squared error of approximation
      90% CI, lower bound |      0.000
      upper bound |      0.097
      pclose |      0.360      Probability RMSEA <= 0.05
-----+-----
Information criteria |
      AIC |      10130.083      Akaike's information criterion
      BIC |      10200.518      Bayesian information criterion
-----+-----
Baseline comparison |
      CFI |      0.986      Comparative fit index
      TLI |      0.974      Tucker-Lewis index
-----+-----
Size of residuals  |

```

SRMR	0.029	Standardized root mean squared residual
CD	0.950	Coefficient of determination

---

## Modification Indices

- MIs are used to check for paths and covariances that could be added to the model to improve model fit
  - ◊ Over-fitting is a serious danger here
- Approximate change in the  $\chi^2$  statistic if the parameter is added to the model
- To obtain modification indices for our model we can type

```
. estat mindices
```

```
Modification indices
```

		MI	df	P>MI	EPC	Standard EPC
Measurement						
paragraph	Spatial	4.815	1	0.03	.0915926	.1377239
sentence	Spatial	12.089	1	0.00	-.215882	-.2196211
cov(e.visual,e.paragraph)		5.118	1	0.02	1.903032	.2039627
cov(e.visual,e.sentence)		5.506	1	0.02	-2.867484	-.2678056
cov(e.paragraph,e.wordc)		12.089	1	0.00	-4.494894	-.5902503
cov(e.sentence,e.wordc)		4.815	1	0.03	4.997621	.571866

EPC = expected parameter change

- The largest MIs are associated with
  - ◊ Adding a path from Spatial to sentence
  - ◊ Adding a covariance between the error terms for paragraph and wordc (word classification)

## Refitting our Model

- We can use the var() option to add the suggested covariance between error terms
- In this case we use var(e.paragraph\*e.wordc)

```
. sem (Spatial -> visual cubes paper) ///
      (Verbal -> paragraph sentence wordc), ///
      var(e.paragraph*e.wordc)
```

Endogenous variables

Measurement: visual cubes paper paragraph sentence wordc

Exogenous variables

Latent: Spatial Verbal



- After fitting the model we could check model fit to see if our model fits better. We could also check the MIs again.
- 

## Full Structural Equation Models

- Combine path analysis and confirmatory factor analysis
  - One or more latent variables are included in the model with corresponding observed indicators
  - Structural relationships may exist among latent and/or observed variables
- 

## Data on Alienation

- The data for this set of examples come from Wheaton et al. (1977)

```
. use wheaton
. ssd describe
```

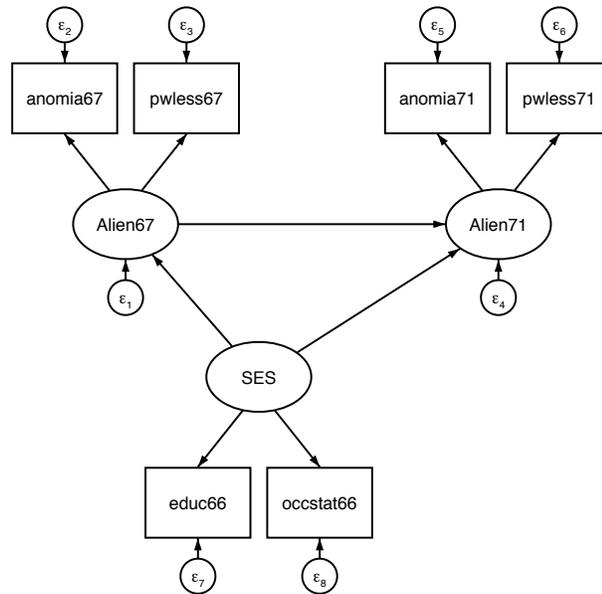
(Structural model with measurement component)

```
Summary statistics data from wheaton.dta
  obs:          932          Structural model with measurem..
  vars:          13          8 Jun 2012 11:28
                              (_dta has notes)
```

```
-----
variable name          variable label
-----
educ66                 Education, 1966
occstat66              Occupational status, 1966
anomia66              Anomia, 1966
pwless66              Powerlessness, 1966
socdist66             Latin American social distance, 1966
occstat67              Occupational status, 1967
anomia67              Anomia, 1967
pwless67              Powerlessness, 1967
socdist67             Latin American social distance, 1967
occstat71              Occupational status, 1971
anomia71              Anomia, 1971
pwless71              Powerlessness, 1971
socdist71             Latin American social distance, 1971
-----
```

- The model includes three latent variables with structural paths between them
  - Alienation in 1971 is predicted by alienation in 1967 and socioeconomic status in 1966
  - In each year, alienation is measured by observed variables measuring feelings of anomia and powerlessness
  - Socioeconomic status is measured by education level and occupational status
-

## The Alienation Model



## Fitting a SEM Model

- Fit the model

```

. sem (Alien67 -> anomia67 pwless67) ///
      (Alien71 -> anomia71 pwless71) ///
      (SES -> educ66 occstat66) ///
      (Alien67 <- SES) ///
      (Alien71 <- Alien67 SES)
  
```

Endogenous variables

Measurement: anomia67 pwless67 anomia71 pwless71 educ66 occstat66  
 Latent: Alien67 Alien71

Exogenous variables

Latent: SES

Fitting target model:

```

Iteration 0: log likelihood = -15249.988
Iteration 1: log likelihood = -15246.584
Iteration 2: log likelihood = -15246.469
Iteration 3: log likelihood = -15246.469
  
```

```

Structural equation model          Number of obs   =       932
Estimation method   = ml
Log likelihood       = -15246.469
  
```

```

( 1) [anomia67]Alien67 = 1
( 2) [anomia71]Alien71 = 1
( 3) [educ66]SES = 1
  
```

-----  
 | OIM

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----						
Structural						
Alien67						
SES	-.6140404	.0562407	-10.92	0.000	-.7242701	-.5038107
-----						
Alien71						
Alien67	.7046342	.0533512	13.21	0.000	.6000678	.8092007
SES	-.1744153	.0542489	-3.22	0.001	-.2807413	-.0680894
-----						
Measurement						
anomia67						
Alien67	1	(constrained)				
_cons	13.61	.1126205	120.85	0.000	13.38927	13.83073
-----						
pwless67						
Alien67	.8884887	.0431565	20.59	0.000	.8039034	.9730739
_cons	14.67	.1001798	146.44	0.000	14.47365	14.86635
-----						
anomia71						
Alien71	1	(constrained)				
_cons	14.13	.1158943	121.92	0.000	13.90285	14.35715
-----						
pwless71						
Alien71	.8486022	.0415205	20.44	0.000	.7672235	.9299808
_cons	14.9	.1034537	144.03	0.000	14.69723	15.10277
-----						
educ66						
SES	1	(constrained)				
_cons	10.9	.1014894	107.40	0.000	10.70108	11.09892
-----						
occstat66						
SES	5.331259	.4307503	12.38	0.000	4.487004	6.175514
_cons	37.49	.6947112	53.96	0.000	36.12839	38.85161
-----						
var(e.anomia67)	4.009921	.3582978			3.365724	4.777416
var(e.pwless67)	3.187468	.283374			2.677762	3.794197
var(e.anomia71)	3.695593	.3911512			3.003245	4.54755
var(e.pwless71)	3.621531	.3037908			3.072483	4.268693
var(e.educ66)	2.943819	.5002527			2.109908	4.107319
var(e.occstat66)	260.63	18.24572			227.2139	298.9605
var(e.Alien67)	5.301416	.483144			4.434225	6.338201
var(e.Alien71)	3.737286	.3881546			3.048951	4.581019
var(SES)	6.65587	.6409484			5.511067	8.038482
-----						
LR test of model vs. saturated:	chi2(6)	=	71.62,	Prob >	chi2 =	0.0000

## Revising the Model

- On substantive grounds we could argue that covariances should be added between the errors for
  - ◇ Powerlessness in 1967 and 1971
  - ◇ Anomia in 1967 and 1971
- One method of evaluating whether adding these covariances to the model improves model fit is to perform a likelihood-ratio test

◇ In the SEM literature this is often called the  $\chi^2$  difference test

- We can use the `lrtest` command to perform this test
- First we will need to fit both models

---

## The Likelihood-ratio Test

- We'll start by storing the estimates from the model we have already run

```
. estimates store nocov
```

- Now we can run the model with the covariances added

```
. sem (Alien67 -> anomia67 pwless67) ///  
      (Alien71 -> anomia71 pwless71) ///  
      (SES -> educ66 occstat66) ///  
      (Alien67 <- SES) ///  
      (Alien71 <- Alien67 SES), ///  
      cov(e.anomia67*e.anomia71 ///  
          e.pwless67*e.pwless71)
```

Endogenous variables

Measurement:  anomia67 pwless67 anomia71 pwless71 educ66 occstat66  
Latent:       Alien67 Alien71

Exogenous variables

Latent:       SES

Fitting target model:

```
Iteration 0:  log likelihood = -15249.988  
Iteration 1:  log likelihood = -15217.95  
Iteration 2:  log likelihood = -15213.126  
Iteration 3:  log likelihood = -15213.046  
Iteration 4:  log likelihood = -15213.046
```

```
Structural equation model                   Number of obs     =       932  
Estimation method     = ml  
Log likelihood         = -15213.046
```

```
( 1) [anomia67]Alien67 = 1  
( 2) [anomia71]Alien71 = 1  
( 3) [educ66]SES = 1
```

```
-----  
-  
                                  |                  OIM  
                                  |          Coef.  Std. Err.    z    P>|z|    [95% Conf. Interval  
> ]  
-----+-----  
-  
Structural                          |  
  Alien67                          |  
          SES | -1.5752228    .057961    -9.92   0.000    -1.6888244   -1.461621  
> 3  
-----+-----  
-  
  Alien71                          |
```

```

      Alien67 |   .606954   .0512305   11.85   0.000   .5065439   .70736
> 4
      SES |  -.2270301   .0530773   -4.28   0.000   -.3310596   -.123000
> 6
-----+-----
-
Measurement
  anomia67 |
      Alien67 |           1 (constrained)
      _cons |    13.61   .1126143   120.85   0.000   13.38928   13.8307
> 2
-----+-----
-
  pwless67 |
      Alien67 |   .9785952   .0619825   15.79   0.000   .8571117   1.10007
> 9
      _cons |    14.67   .1001814   146.43   0.000   14.47365   14.8663
> 5
-----+-----
-
  anomia71 |
      Alien71 |           1 (constrained)
      _cons |    14.13   .1159036   121.91   0.000   13.90283   14.3571
> 7
-----+-----
-
  pwless71 |
      Alien71 |   .9217508   .0597225   15.43   0.000   .8046968   1.03880
> 5
      _cons |    14.9   .1034517   144.03   0.000   14.69724   15.1027
> 6
-----+-----
-
  educ66 |
      SES |           1 (constrained)
      _cons |    10.9   .1014894   107.40   0.000   10.70108   11.0989
> 2
-----+-----
-
  occstat66 |
      SES |    5.22132   .425595   12.27   0.000   4.387169   6.05547
> 1
      _cons |    37.49   .6947112   53.96   0.000   36.12839   38.8516
> 1
-----+-----
-
      var(e.anomia67)|  4.728874   .456299           3.914024   5.71336
> 5
      var(e.pwless67)|  2.563413   .4060733           1.879225   3.496
> 7
      var(e.anomia71)|  4.396081   .5171156           3.490904   5.53596
> 6
      var(e.pwless71)|  3.072085   .4360333           2.326049   4.05739
> 8
      var(e.educ66)|  2.803674   .5115854           1.960691   4.00909
> 1
      var(e.occstat66)| 264.5311   18.22483           231.1177   302.775
> 1
      var(e.Alien67)|  4.842059   .4622537           4.015771   5.83836
> 4

```

```

                var(e.Alien71)|  4.084249  .4038995                3.364613  4.95780
> 2
                var(SES)|  6.796014  .6524866                5.630283  8.20310
> 5
-----+-----
-
cov(e.anomia67,e.anomia71)|  1.622024  .3154267    5.14  0.000    1.003799  2.24024
> 9
cov(e.pwless67,e.pwless71)|  .3399961  .2627541    1.29  0.196   -0.1749925  .854984
> 7
-----
-
LR test of model vs. saturated: chi2(4) =      4.78, Prob > chi2 = 0.3111

```

- First we store the estimates

```
. estimates store withcov
```

### The Likelihood-ratio Test (Continued)

- Then we can run the likelihood ratio test

```
. lrtest nocov withcov
```

```

Likelihood-ratio test                    LR chi2(2) =    66.85
(Assumption: nocov nested in withcov)   Prob > chi2 =    0.0000

```

- The likelihood-ratio test indicates significantly better fit with the two covariances
- We could also have run only the model with the covariances and used the test command to perform a Wald test for joint significance of the covariances

## 2.4 Multiple Group Models

### Comparing Groups

- Multiple group SEM allows for estimating parameters of a model separately for across groups
  - ◇ All parameters may be estimated separately, or
  - ◇ Some or all parameters can be constrained to equality across groups
- This allows us to examine whether parameters vary across groups
- We can use the group() option of sem to fit a model for two or more groups
- The ginvariant() option allows you to specify what parameters should be constrained across groups
  - ◇ By default measurement coefficients and measurement intercepts are constrained across groups

## Multiple Group CFA

- To demonstrate we will return to the two-factor CFA model we fit earlier

```
. use hsdata, clear
```

```
(Data from Holzinger and Swineford (1939))
```

- The students in this dataset come from two different schools

```
. tab school
```

school	Freq.	Percent	Cum.
Pasteur	156	51.83	51.83
Grant-White	145	48.17	100.00
Total	301	100.00	

---

## A Model with No Cross-group Constraints

- We will begin by estimating all parameters separately for each group to do this we will
  - ◇ Specify `ginvariant(none)`
  - ◇ Set the means of the latent variables to 0 using the `mean()` option
- Our command is

```
. sem (Spatial -> visual cubes paper) ///  
      (Verbal -> paragraph sentence wordc), ///  
      mean(Spatial@0 Verbal@0) ///  
      group(school) ginvariant(none)
```

```
Endogenous variables
```

```
Measurement:  visual cubes paper paragraph sentence wordc
```

```
Exogenous variables
```

```
Latent:      Spatial Verbal
```

```
Fitting target model:
```

```
Iteration 0:  log likelihood = -5018.5723  
Iteration 1:  log likelihood = -5017.9684  
Iteration 2:  log likelihood = -5017.9585  
Iteration 3:  log likelihood = -5017.9585
```

```
Structural equation model          Number of obs    =      301  
Grouping variable = school         Number of groups =       2  
Estimation method = ml  
Log likelihood    = -5017.9585
```

```
( 1) [visual]1bn.school#c.Spatial = 1  
( 2) [paragraph]1bn.school#c.Verbal = 1  
( 3) [/]mean(Spatial)#1bn.school = 0  
( 4) [/]mean(Verbal)#1bn.school = 0  
( 5) [visual]2.school#c.Spatial = 1  
( 6) [paragraph]2.school#c.Verbal = 1  
( 7) [/]mean(Spatial)#2.school = 0
```

( 8) [ / ] mean(Verbal)#2.school = 0

Group : Pasteur Number of obs = 156

		Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
Measurement							
visual							
	Spatial	1	(constrained)				
	_cons	29.64744	.5674292	52.25	0.000	28.5353	30.75958
cubes							
	Spatial	.2712034	.1027351	2.64	0.008	.0698463	.4725605
	_cons	23.9359	.3927222	60.95	0.000	23.16618	24.70562
paper							
	Spatial	.1973023	.0641721	3.07	0.002	.0715272	.3230774
	_cons	14.16026	.227089	62.36	0.000	13.71517	14.60534
paragraph							
	Verbal	1	(constrained)				
	_cons	8.467949	.2759271	30.69	0.000	7.927142	9.008756
sentence							
	Verbal	1.574508	.1457788	10.80	0.000	1.288787	1.860229
	_cons	15.98077	.4185334	38.18	0.000	15.16046	16.80108
wordc							
	Verbal	1.365996	.1459215	9.36	0.000	1.079996	1.651997
	_cons	24.19872	.4216584	57.39	0.000	23.37228	25.02515
	mean(Spatial)	0	(constrained)				
	mean(Verbal)	0	(constrained)				
	var(e.visual)	13.00047	10.01906			2.870547	58.87808
	var(e.cubes)	21.32184	2.625654			16.7496	27.14219
	var(e.paper)	6.595619	.8718128			5.090299	8.546098
	var(e.paragraph)	3.715095	.6950598			2.574649	5.360704
	var(e.sentence)	7.092144	1.564653			4.602432	10.92868
	var(e.wordc)	12.50614	1.783697			9.456279	16.53966
	var(Spatial)	37.22777	11.33104			20.50153	67.60016
	var(Verbal)	8.162082	1.392037			5.842909	11.40178
	cov(Spatial,Verbal)	8.594239	2.055358	4.18	0.000	4.565812	12.62267

Group : Grant-White Number of obs = 145

		Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
Measurement							
visual							
	Spatial	1	(constrained)				
	_cons	29.57931	.5721785	51.70	0.000	28.45786	30.70076
cubes							

```

      Spatial | .3769229 .1031886 3.65 0.000 .1746769 .5791688
      _cons | 24.8 .3678649 67.42 0.000 24.079 25.521
-----+-----
paper
      Spatial | .3004087 .0787246 3.82 0.000 .1461113 .4547062
      _cons | 14.30345 .2335324 61.25 0.000 13.84573 14.76116
-----+-----
paragraph
      Verbal | 1 (constrained)
      _cons | 9.951724 .2793454 35.63 0.000 9.404217 10.49923
-----+-----
sentence
      Verbal | 1.550538 .1540779 10.06 0.000 1.248551 1.852525
      _cons | 18.84828 .3847671 48.99 0.000 18.09415 19.60241
-----+-----
wordc
      Verbal | 1.392518 .1663741 8.37 0.000 1.066431 1.718605
      _cons | 28.2 .4433791 63.60 0.000 27.33099 29.06901
-----+-----
      mean(Spatial) | 0 (constrained)
      mean(Verbal) | 0 (constrained)
-----+-----
      var(e.visual) | 23.07059 6.254186 13.56149 39.24734
      var(e.cubes) | 16.15544 2.130434 12.47585 20.92029
      var(e.paper) | 5.705868 .8699284 4.232001 7.693034
      var(e.paragraph) | 4.150919 .7114099 2.966608 5.808024
      var(e.sentence) | 4.243196 1.346801 2.277821 7.904358
      var(e.wordc) | 14.61309 2.026313 11.13553 19.17667
      var(Spatial) | 24.4007 7.450847 13.41173 44.39356
      var(Verbal) | 7.163992 1.340404 4.964697 10.33754
-----+-----
      cov(Spatial,Verbal) | 7.303571 1.806168 4.04 0.000 3.763546 10.8436
-----+-----
LR test of model vs. saturated: chi2(16) = 27.86, Prob > chi2 = 0.0328

```

### Testing for Group Differences

- We could use a likelihood-ratio test to see whether the parameters vary across schools
- An alternative is to use `estat ginvariant` instead
  - ◊ Wald tests are used to test whether *unconstrained* coefficients are significantly different
  - ◊ Score tests are used to test whether *relaxing constraints* would improve model fit
  - ◊ In both cases the null hypothesis is that the constraint does not harm model fit
- Let's give it a try

```
. estat ginvariant
```

```
Tests for group invariance of parameters
```

```

-----+-----
      |           Wald Test           Score Test
      |           chi2           df           p>chi2           chi2           df           p>chi2
-----+-----
Measurement
visual
      Spatial | . . . . 0 .

```

	_cons		0.007	1	0.9326	.	.	.
-----								
cubes								
	Spatial		0.527	1	0.4678	.	.	.
	_cons		2.579	1	0.1083	.	.	.
-----								
paper								
	Spatial		1.031	1	0.3100	.	.	.
	_cons		0.193	1	0.6602	.	.	.
-----								
paragraph								
	Verbal		.	.	.	.	0	.
	_cons		14.280	1	0.0002	.	.	.
-----								
sentence								
	Verbal		0.013	1	0.9100	.	.	.
	_cons		25.440	1	0.0000	.	.	.
-----								
wordc								
	Verbal		0.014	1	0.9046	.	.	.
	_cons		42.765	1	0.0000	.	.	.
-----								
	mean(Spatial)		.	.	.	.	0	.
	mean(Verbal)		.	.	.	.	0	.
-----								
	var(e.visual)		0.727	1	0.3939	.	.	.
	var(e.cubes)		2.335	1	0.1265	.	.	.
	var(e.paper)		0.522	1	0.4700	.	.	.
	var(e.paragraph)		0.192	1	0.6612	.	.	.
	var(e.sentence)		1.904	1	0.1676	.	.	.
	var(e.wordc)		0.609	1	0.4351	.	.	.
	var(Spatial)		0.895	1	0.3442	.	.	.
	var(Verbal)		0.267	1	0.6055	.	.	.
-----								
	cov(Spatial,Verbal)		0.223	1	0.6371	.	.	.
-----								

- We fail to reject the null hypothesis that the measurement coefficients are the same across groups

---

### Constraining Coefficients

- We could refit the model constraining measurement coefficients to equality across groups using the option `ginvariant(mcoef)`
- Then we could use `estat ginvariant` to test for equality of the intercepts across groups
- A typical ordering of tests is
  - ◊ Measurement coefficients
  - ◊ Measurement intercepts
  - ◊ Measurement error variances

---

## 3 Generalized SEM

### 3.1 Introduction

#### Generalized Structure Equation Models

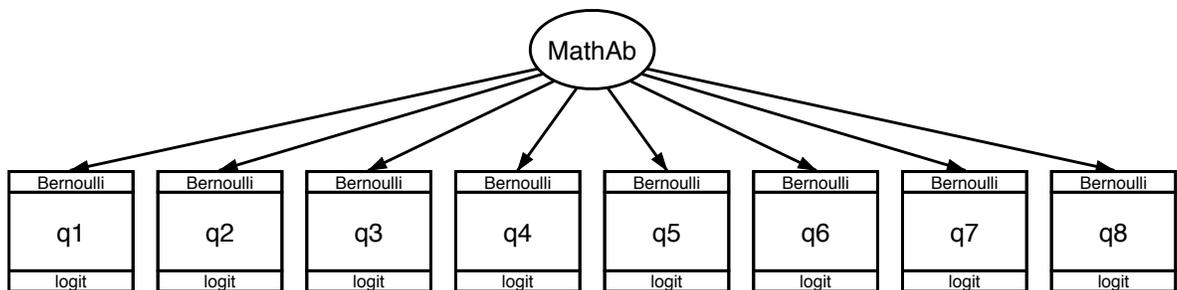
- gsem allows us to extend the types of models we can fit
- Models for binary, ordered, nominal, count, survival time, interval, and censored responses.
- Multilevel models, including models with random intercepts and slopes, for nested or crossed data
- Latent variables can be included at any level of the model

## 3.2 Models for Generalized Responses

### CFA with Binary Indicators

- Many of the models we fit above can be extended to include generalized response variables
- In this example we will fit a confirmatory factor analysis model using binary indicators
- The dataset contains fictional data on students' math scores and attitudes towards math
- The binary indicators are 8 questions from a math test
- The latent variable is math ability

### Path Model for a Generalized CFA



### Fitting a Generalized CFA

- Let's begin by opening the dataset and looking at the items q1-q8

```
. use math
. codebook q1-q8
```

(Fictional math abilities data)

```
-----
q1                                     q1 correct
-----
```

```

      type: numeric (byte)
      label: result

      range: [0,1]
      unique values: 2

      units: 1
      missing .: 0/500
```

```

tabulation: Freq.  Numeric  Label
             247      0  Incorrect
             253      1  Correct

```

-----  
q2  
-----

```

type: numeric (byte)
label: result

range: [0,1]          units: 1
unique values: 2      missing .: 0/500

```

```

tabulation: Freq.  Numeric  Label
             303      0  Incorrect
             197      1  Correct

```

-----  
q3  
-----

```

type: numeric (byte)
label: result

range: [0,1]          units: 1
unique values: 2      missing .: 0/500

```

```

tabulation: Freq.  Numeric  Label
             233      0  Incorrect
             267      1  Correct

```

-----  
q4  
-----

```

type: numeric (byte)
label: result

range: [0,1]          units: 1
unique values: 2      missing .: 0/500

```

```

tabulation: Freq.  Numeric  Label
             288      0  Incorrect
             212      1  Correct

```

-----  
q5  
-----

```

type: numeric (byte)
label: result

range: [0,1]          units: 1
unique values: 2      missing .: 0/500

```

```

tabulation: Freq.  Numeric  Label
             255      0  Incorrect
             245      1  Correct

```

-----  
q6 q6 correct  
-----

```
      type: numeric (byte)
      label: result

      range: [0,1]                units: 1
unique values: 2                missing .: 0/500

      tabulation: Freq.  Numeric  Label
                  283      0  Incorrect
                  217      1  Correct
```

-----  
q7 q7 correct  
-----

```
      type: numeric (byte)
      label: result

      range: [0,1]                units: 1
unique values: 2                missing .: 0/500

      tabulation: Freq.  Numeric  Label
                  240      0  Incorrect
                  260      1  Correct
```

-----  
q8 q8 correct  
-----

```
      type: numeric (byte)
      label: result

      range: [0,1]                units: 1
unique values: 2                missing .: 0/500

      tabulation: Freq.  Numeric  Label
                  253      0  Incorrect
                  247      1  Correct
```

- There are only a few changes to the command
  - ◊ We will use the `gsem` command to fit this model
  - ◊ Specify the `logit` option to fit a logit model to our binary response variables q1-q8
  - ◊ We'll use the `nodvheader`, otherwise `gsem` will list the family and link function for each dependent variable

```
. gsem (MathAb -> q1-q8, logit), nodvheader
```

Fitting fixed-effects model:

```
Iteration 0:  log likelihood = -2750.3114
Iteration 1:  log likelihood = -2749.3709
Iteration 2:  log likelihood = -2749.3708
```

Refining starting values:

```
Grid node 0:  log likelihood = -2645.8536
```

Fitting full model:

```
Iteration 0: log likelihood = -2645.8536
Iteration 1: log likelihood = -2638.477
Iteration 2: log likelihood = -2637.6526
Iteration 3: log likelihood = -2637.3803
Iteration 4: log likelihood = -2637.376
Iteration 5: log likelihood = -2637.3759
```

```
Generalized structural equation model      Number of obs      =      500
Log likelihood = -2637.3759
```

( 1) [q1]MathAb = 1

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----						
q1						
MathAb	1	(constrained)				
_cons	.0373365	.1252279	0.30	0.766	-.2081058	.2827787
-----						
q2						
MathAb	.381626	.116809	3.27	0.001	.1526845	.6105674
_cons	-.4613391	.0989722	-4.66	0.000	-.655321	-.2673571
-----						
q3						
MathAb	.4993762	.134314	3.72	0.000	.2361255	.7626269
_cons	.1533362	.1006072	1.52	0.127	-.0438503	.3505228
-----						
q4						
MathAb	.3299698	.1063034	3.10	0.002	.1216189	.5383207
_cons	-.3230667	.0957983	-3.37	0.001	-.510828	-.1353054
-----						
q5						
MathAb	.8401762	.1995336	4.21	0.000	.4490975	1.231255
_cons	-.0494684	.1163093	-0.43	0.671	-.2774304	.1784937
-----						
q6						
MathAb	.6453722	.1639865	3.94	0.000	.3239646	.9667798
_cons	-.314723	.1083049	-2.91	0.004	-.5269968	-.1024493
-----						
q7						
MathAb	.8163613	.2045448	3.99	0.000	.4154609	1.217262
_cons	.1053404	.1152979	0.91	0.361	-.1206393	.3313201
-----						
q8						
MathAb	.5769516	.1473524	3.92	0.000	.2881463	.865757
_cons	-.026705	.1034396	-0.26	0.796	-.2294429	.1760328
-----						
var(MathAb)	2.151059	.7298407			1.106229	4.182728
-----						

- If we include certain constraints on this model, it can be interpreted as an item response theory (IRT) model
  - ◇ See help irt for information on Stata's irt commands

## A Generalized Structural Equation Model

- The dataset also includes information on student's attitudes towards math, we may want to see if these predict math ability
- Let's look more closely at these items

```
. codebook att*
```

```
-----
att1                               Skills taught in math class will help me get a better job.
-----
```

```

      type: numeric (float)
      label: agree

      range: [1,5]                units: 1
unique values: 5                  missing .: 0/500

```

```

tabulation: Freq.  Numeric  Label
              150         1  Strongly disagree
              78         2   Disagree
              52         3 Neither agree nor disagree
              89         4   Agree
              131         5 Strongly agree

```

```
-----
att2                               Math is important in everyday life
-----
```

```

      type: numeric (float)
      label: agree

      range: [1,5]                units: 1
unique values: 5                  missing .: 0/500

```

```

tabulation: Freq.  Numeric  Label
              134         1  Strongly disagree
              93         2   Disagree
              65         3 Neither agree nor disagree
              81         4   Agree
              127         5 Strongly agree

```

```
-----
att3                               Working math problems makes me anxious.
-----
```

```

      type: numeric (float)
      label: agree

      range: [1,5]                units: 1
unique values: 5                  missing .: 0/500

```

```

tabulation: Freq.  Numeric  Label
              171         1  Strongly disagree
              75         2   Disagree
              47         3 Neither agree nor disagree
              77         4   Agree
              130         5 Strongly agree

```

```
-----
att4                               Math has always been my worst subject.
-----
```

```

type: numeric (float)
label: agree

range: [1,5]
unique values: 5

units: 1
missing .: 0/500

tabulation: Freq. Numeric Label
            145      1 Strongly disagree
            83       2 Disagree
            63       3 Neither agree nor disagree
            90       4 Agree
            119      5 Strongly agree

```

---

```

att5 I am able to learn new math concepts easily.

```

---

```

type: numeric (float)
label: agree

range: [1,5]
unique values: 5

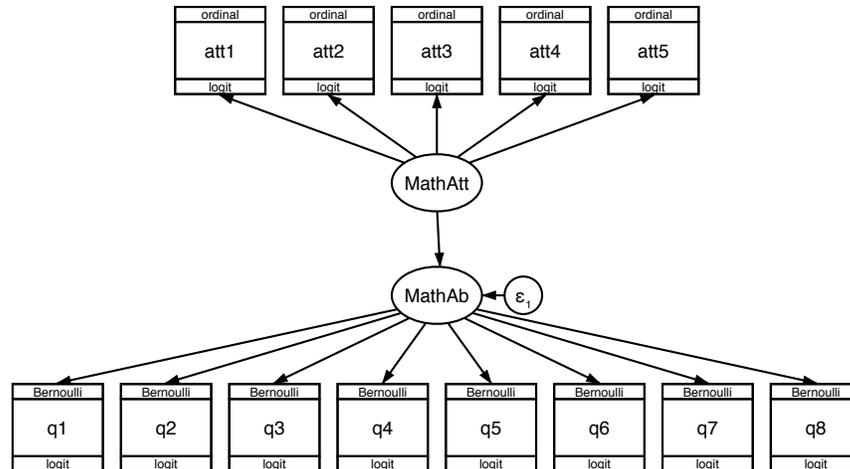
units: 1
missing .: 0/500

tabulation: Freq. Numeric Label
            121      1 Strongly disagree
            91       2 Disagree
            62       3 Neither agree nor disagree
            76       4 Agree
            150      5 Strongly agree

```

- The math attitude items appear to be Likert-type items

### Path Diagram for the GSEM



## Fitting a GSEM

- We will use the `ologit` option to model the responses `att1-att5` using an ordered logistic model

```
. gsem (MathAb -> q1-q8, logit) ///
      (MathAtt -> att1-att5, ologit) ///
      (MathAtt -> MathAb), nodvheader
```

Fitting fixed-effects model:

```
Iteration 0: log likelihood = -6629.7253
Iteration 1: log likelihood = -6628.7848
Iteration 2: log likelihood = -6628.7848
```

Refining starting values:

```
Grid node 0: log likelihood = -6429.1636
```

Fitting full model:

```
Iteration 0: log likelihood = -6429.1636
Iteration 1: log likelihood = -6396.7471
Iteration 2: log likelihood = -6394.6197
Iteration 3: log likelihood = -6394.3949
Iteration 4: log likelihood = -6394.3923
Iteration 5: log likelihood = -6394.3923
```

```
Generalized structural equation model          Number of obs    =          500
Log likelihood = -6394.3923
```

```
( 1) [q1]MathAb = 1
( 2) [att1]MathAtt = 1
```

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
q1	MathAb	1 (constrained)					
	_cons	.044612	.1272967	0.35	0.726	-.204885	.294109
q2	MathAb	.3446066	.1050261	3.28	0.001	.1387593	.550454
	_cons	-.4572215	.0979965	-4.67	0.000	-.6492911	-.2651519
q3	MathAb	.5445222	.1386992	3.93	0.000	.2726767	.8163677
	_cons	.1591406	.1033116	1.54	0.123	-.0433465	.3616276
q4	MathAb	.2858862	.0948549	3.01	0.003	.099974	.4717984
	_cons	-.3196648	.0947684	-3.37	0.001	-.5054075	-.1339222
q5	MathAb	.8174769	.1867022	4.38	0.000	.4515473	1.183406
	_cons	-.04543	.116575	-0.39	0.697	-.2739129	.1830528
q6	MathAb	.6030423	.1471949	4.10	0.000	.3145457	.8915389
	_cons	-.3099919	.1070853	-2.89	0.004	-.5198754	-.1001085
q7	MathAb	.7208369	.171309	4.21	0.000	.3850774	1.056597

	_cons		.1047264	.1116494	0.94	0.348	-.1141024	.3235553
q8	MathAb		.5814736	.1426725	4.08	0.000	.3018406	.8611067
	_cons		-.0250443	.1045135	-0.24	0.811	-.2298869	.1797984
att1	MathAtt		1 (constrained)					
att2	MathAtt		.3788715	.0971234	3.90	0.000	.1885131	.5692299
att3	MathAtt		-1.592717	.3614956	-4.41	0.000	-2.301236	-.8841989
att4	MathAtt		-.8100108	.1530675	-5.29	0.000	-1.110017	-.510004
att5	MathAtt		.5225425	.1170166	4.47	0.000	.2931942	.7518907
MathAb	MathAtt		.581103	.14776	3.93	0.000	.2914987	.8707072
/att1	cut1		-1.10254	.131228			-1.359742	-.8453377
	cut2		-.2495339	.1160385			-.4769652	-.0221025
	cut3		.2983261	.1164415			.070105	.5265472
	cut4		1.333052	.1391919			1.060241	1.605864
/att2	cut1		-1.055791	.1062977			-1.264131	-.8474513
	cut2		-.1941211	.0941435			-.378639	-.0096032
	cut3		.3598488	.0952038			.1732528	.5464448
	cut4		1.132624	.1082204			.9205156	1.344732
/att3	cut1		-1.053519	.1734001			-1.393377	-.7136612
	cut2		-.0491074	.1442846			-.3319	.2336853
	cut3		.5570672	.1538702			.2554871	.8586472
	cut4		1.666859	.2135557			1.248297	2.08542
/att4	cut1		-1.07378	.1214071			-1.311734	-.8358264
	cut2		-.2112462	.1076501			-.4222365	-.0002559
	cut3		.406347	.1094847			.191761	.620933
	cut4		1.398185	.1313327			1.140778	1.655593
/att5	cut1		-1.244051	.1148443			-1.469142	-1.018961
	cut2		-.336135	.0986678			-.5295203	-.1427498
	cut3		.2137776	.0978943			.0219084	.4056468
	cut4		.9286849	.107172			.7186316	1.138738
	var(e.MathAb)		1.787117	.5974753			.9280606	3.441357
	var(MathAtt)		1.520854	.4077885			.8991947	2.572298

### 3.3 Multilevel Models

#### Multilevel SEM

- Many of the types of structural equation models that we have discussed can be extended to multilevel models using `gsem`
  - Because `gsem` can be used to include random effects and model generalized responses a large number of models can be fit
    - ◊ Including a multilevel multinomial logit model that cannot be fit elsewhere
- 

#### Multilevel CFA

- We will look at an example of a multilevel CFA
- We will continue using the the same dataset
- The students are clustered within schools
- This time we will measure the latent variable `MathAb` using test scores, let's take a look

```
. codebook school test*
```

```
-----  
school                                                    School id  
-----  
  
                type: numeric (byte)  
  
                range: [1,20]                units: 1  
unique values: 20                missing .: 0/500  
  
                mean: 10.5  
                std. dev: 5.77206  
  
percentiles:      10%      25%      50%      75%      90%  
                  2.5      5.5      10.5     15.5     18.5  
  
-----  
test1                                                    Score, math test 1  
-----  
  
                type: numeric (byte)  
  
                range: [55,93]                units: 1  
unique values: 36                missing .: 0/500  
  
                mean: 75.548  
                std. dev: 5.94865  
  
percentiles:      10%      25%      50%      75%      90%  
                  68      72      76      79      83  
  
-----  
test2                                                    Score, math test 2  
-----  
  
                type: numeric (byte)
```

```

        range: [65,94]                units: 1
unique values: 28                    missing .: 0/500

        mean:    80.556
        std. dev: 4.97679

percentiles:    10%    25%    50%    75%    90%
                74     77     80     84     88

```

---

```
test3                                     Score, math test 3
```

---

```

        type: numeric (byte)

        range: [50,94]                units: 1
unique values: 36                    missing .: 0/500

        mean:    75.572
        std. dev: 6.67787

percentiles:    10%    25%    50%    75%    90%
                67     71.5   76     80     84

```

---

```
test4                                     Score, math test 4
```

---

```

        type: numeric (byte)

        range: [43,96]                units: 1
unique values: 48                    missing .: 0/500

        mean:    74.078
        std. dev: 8.84559

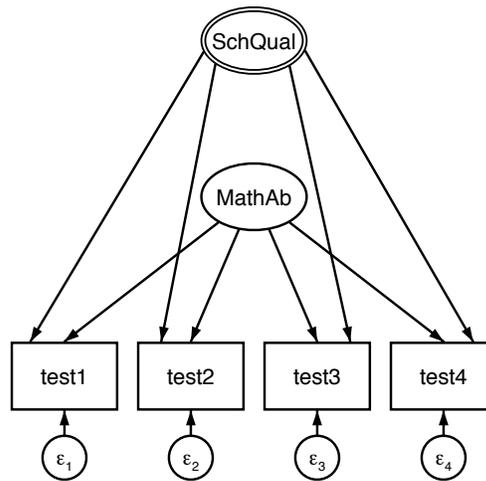
percentiles:    10%    25%    50%    75%    90%
                63     69     74     80     86

```

---

### Path Diagram for a Multilevel CFA

- Random effects are denoted as ovals with double rings
- Graphically the model is



### Fitting a Multilevel CFA

- Here the test items are predicted by MathAb and the random intercept denoted SchQual
- The square brackets around school indicate that SchQual is constant within school and varies across schools
- Run the model

```
. gsem (MathAb SchQual[school] -> test1 test2 test3 test4)
```

Fitting fixed-effects model:

```
Iteration 0: log likelihood = -6569.2088
Iteration 1: log likelihood = -6569.2088
```

Refining starting values:

```
Grid node 0: log likelihood = -5394.8535
```

Fitting full model:

```
Iteration 0: log likelihood = -5394.8535 (not concave)
Iteration 1: log likelihood = -5391.8634
Iteration 2: log likelihood = -5386.954
Iteration 3: log likelihood = -5386.132
Iteration 4: log likelihood = -5386.112
Iteration 5: log likelihood = -5386.1119
```

```
Generalized structural equation model          Number of obs    =      500
```

```
Response      : test1
Family        : Gaussian
Link          : identity
```

```
Response      : test2
Family        : Gaussian
Link          : identity
```

```
Response      : test3
Family        : Gaussian
```

Link : identity

Response : test4

Family : Gaussian

Link : identity

Log likelihood = -5386.1119

( 1) [test1]SchQual[school] = 1

( 2) [test2]MathAb = 1

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----						
test1						
SchQual[school]	1 (constrained)					
MathAb	1.505647	.0781211	19.27	0.000	1.352532	1.658761
_cons	75.97363	.4239572	179.20	0.000	75.14269	76.80457
-----						
test2						
SchQual[school]	.2535074	.1413808	1.79	0.073	-.023594	.5306087
MathAb	1 (constrained)					
_cons	80.83869	.2262333	357.32	0.000	80.39528	81.2821
-----						
test3						
SchQual[school]	.8253025	.0975692	8.46	0.000	.6340704	1.016535
MathAb	1.76592	.0900749	19.61	0.000	1.589377	1.942464
_cons	76.07121	.3911863	194.46	0.000	75.3045	76.83792
-----						
test4						
SchQual[school]	1.352783	.0963211	14.04	0.000	1.163997	1.541569
MathAb	2.394628	.1180165	20.29	0.000	2.16332	2.625936
_cons	74.75494	.5875971	127.22	0.000	73.60327	75.90661
-----						
var(SchQual[school])	2.637378	1.196124			1.084248	6.415285
var(MathAb)	12.00398	1.401103			9.549339	15.08959
-----						
var(e.test1)	3.980296	.2902873			3.450137	4.591921
var(e.test2)	12.46348	.8074865			10.9772	14.151
var(e.test3)	4.087937	.3289069			3.49155	4.786192
var(e.test4)	1.465088	.3576202			.9080087	2.363946
-----						

## 4 Conclusion

### 4.1 Conclusion

#### Conclusion

- We have learned a bit about structural equation models and generalized structural equation models
- We have seen how to use `sem` to fit linear SEM models
- We have also seen how `gsem` can be used to fit more general models
- We have also touched on the flexibility of `gsem`



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