Structural Equation Modeling (SEM)

223

Structural Equation Modeling (SEM)

Used to study relationships among multiple outcomes often involving latent variables

- Estimate and test direct and indirect effects in a system of regression equations for latent variables without the influence of measurement error
- Estimate and test theories about the absence of relationships among latent variables

Model identification, estimation, testing, and modification are the same as for CFA.

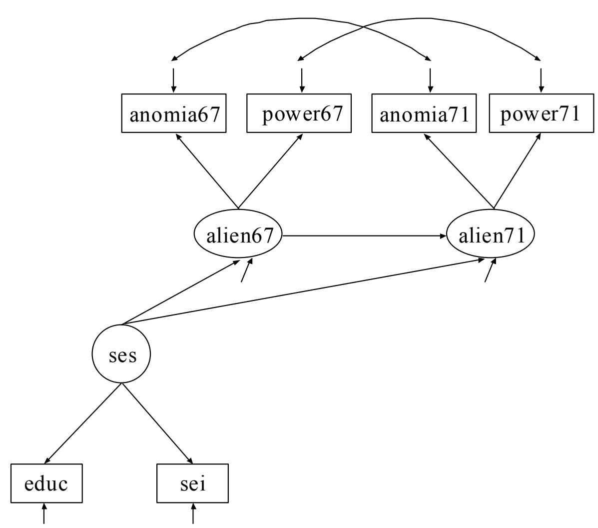
224

Steps In SEM

- Establish a CFA model when latent variables are involved
- Establish a model of the relationships among the observed or latent variables
- Modify the model

225

Classic Wheaton Et Al. SEM



226

Input For Classic Wheaton Et Al. SEM

```
TITLE:      Classic structural equation model with multiple
            indicators used in a study of the stability of
            alienation.

DATA:       FILE IS wheacov.dat
            TYPE IS COVARIANCE;
            NOBS ARE 932;

VARIABLE:   NAMES ARE anomia67 power67 anomia71 power71 educ
            sei;

MODEL:      ses       BY educ sei;
            alien67   BY anomia67 power67;
            alien71   BY anomia71 power71;

            alien71   ON alien67 ses;
            alien67   ON ses;

            anomia67  WITH anomia71;
            power67   WITH power71;

OUTPUT:     SAMPSTAT STANDARDIZED MODINDICES (0);
```


Output Excerpts
Classic Wheaton Et Al. SEM

Tests Of Model Fit

```
Chi-Square Test of Model Fit
             Value                               4.771
             Degrees of Freedom                      4
             P-Value                             .3111

RMSEA (Root Mean Square Error Of Approximation)
             Estimate                             .014
             90 Percent C.I.                      .000  .053
             Probability RMSEA <= .05             .928
```

Output Excerpts
Classic Wheaton Et Al. SEM (Continued)

Model Results

	Estimates	S.E.	Est./S.E.	Std	StdYX
SES BY					
EDUC	1.000	.000	.000	2.607	.841
SEI	5.221	.422	12.367	13.612	.642
ALIEN67 BY					
ANOMIA67	1.000	.000	.000	2.663	.775
POWER67	.979	.062	15.896	2.606	.852
ALIEN71 BY					
ANOMIA71	1.000	.000	.000	2.850	.805
POWER71	.922	.059	15.500	2.627	.832

229

Output Excerpts
Classic Wheaton Et Al. SEM (Continued)

ALIEN71 ON					
ALIEN67	.607	.051	11.895	.567	.567
SES	-.227	.052	-4.337	-.208	-.208
ALIEN67 ON					
SES	-.575	.056	-10.197	-.563	-.563
ANOMIA67 WITH					
ANOMIA71	1.622	.314	5.173	1.622	.133
POWER67 WITH					
POWER71	.340	.261	1.302	.340	.035

230

Output Excerpts Classic Wheaton Et Al. SEM (Continued)

	Estimates	S.E.	Est./S.E.	Std	StdYX
Residual Variances					
ANOMIA67	4.730	.453	10.438	4.730	.400
POWER67	2.564	.403	6.362	2.564	.274
ANOMIA71	4.397	.515	8.537	4.397	.351
POWER71	3.072	.434	7.077	3.072	.308
EDUC	2.804	.507	5.532	2.804	.292
SEI	264.532	18.125	14.595	264.532	.588
ALIEN67	4.842	.467	10.359	.683	.683
ALIEN71	4.084	.404	10.104	.503	.503
Variances					
SES	6.796	.649	10.476	1.000	1.000

231

Output Excerpts Classic Wheaton Et Al. SEM (Continued)

R-Square

Observed Variable	R-Square
ANOMIA67	.600
POWER67	.726
ANOMIA71	.649
POWER71	.692
EDUC	.708
SEI	.412

Latent Variable	R-Square
ALIEN67	.317
ALIEN71	.497

232

Modeling Issues In SEM

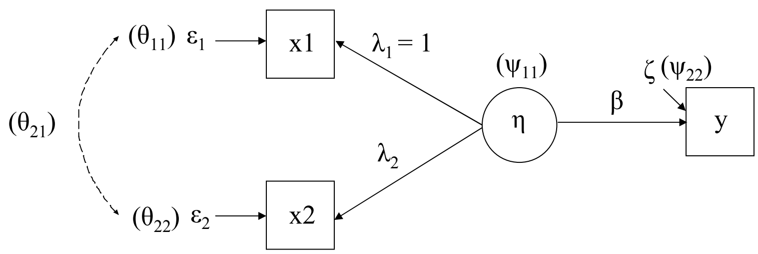
- Model building strategies
  – Bottom up
  – Measurement versus structural parts
- Number of indicators
  – Identifiability
  – Robustness to misspecification
- Believability
  – Measures
  – Direction of arrows
  – Other models
- Quality of estimates
  – Parameters, s.e.'s, power
  – Monte Carlo study within the substantive study

233

Model Identification

234

Model Identification Issues: A (Simple?) SEM With Measurement Errors In The *x*'s



235

Model Identification Issues (Continued)

A non-identified parameter gives a non-invertible information matrix (no s.e.s.; indeterminacy involving parameter #...).

A fixed or constrained parameter with a derivative (MI) different from zero would be identified if freed and would improve F.

Example (alcohol consumption, dietary fat intake, blood pressure):

Two indicators of a single latent variable that predicts a later observed outcome (6 parameters; just identified model):

$$x_{ij} = \lambda_j \eta_i + \varepsilon_{ij} \; (j = 1,2), \qquad (28)$$

$$y_i = \beta \eta_i + \zeta_i. \qquad (29)$$

236

Model Identification Issues (Continued)

Show identification by solving for the parameters in terms of the **Σ** elements (fixing $\lambda_1 = 1$):

$V(x_1) = \sigma_{11} = \psi_{11} + \theta_{11}$, (33) $V(x_2) = \sigma_{22} = \lambda_2^2 \psi_{11} + \theta_{22}$, (34)

$Cov(x_2, x_1) = \sigma_{21} = \lambda_2 \psi_{11}$, (35) $Cov(y, x_1) = \sigma_{31} = \beta \psi_{11}$, (36)

$Cov(y, x_2) = \sigma_{32} = \lambda_2 \beta \psi_{11}$, (37) $V(y) = \sigma_{33} = \beta^2 \psi_{11} + \psi_{22}$. (38)

Solving for β:

$$\frac{Cov(y, x_2)}{Cov(x_2, x_1)} = \frac{\lambda_2 \beta \psi_{11}}{\lambda_2 \psi_{11}} = \beta$$

With correlated error θ_{21}:

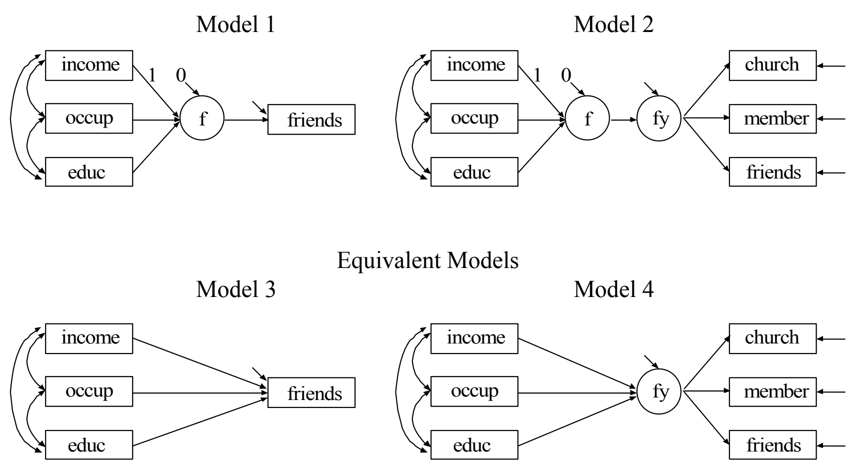
$$\frac{Cov(y, x_2)}{Cov(x_2, x_1)} = \frac{\lambda_2 \beta \psi_{11}}{\lambda_2 \psi_{11} + \theta_{21}} \neq \beta$$

237

Formative Indicators

238

Formative Indicators



239

Hodge-Treiman Social Status Indicators

Social participation related to social status (n = 530 women)

Social participation measures:

- Church membership
- Memberships
- Friends seen

Social status measures:

- Income
- Occupation
- Education

Source: Hodge-Treiman (1968), American Sociological Review

240

Input For Social Status Formative Indicators, Model 1

```
TITLE:       Hodge-Treiman social status modeling

DATA:        FILE = htmimicn1.dat;
             TYPE = COVARIANCE;
             NOBS = 530;

VARIABLE:    NAMES = church member friends income occup educ;
             USEV = friends-educ;

MODEL:       f BY;  ! defining the formative factor
             f ON income@1 occup educ;
             f@0;
             friends ON f;

OUTPUT:      TECH1 STANDARDIZED;
```

241

Output Excerpts Social Status Formative Indicators, Model 1

Tests Of Model Fit

```
Chi-Square Test of Model Fit
             Value                          0.000
             Degrees of Freedom                 0
             P-Value                       0.0000
```

Model Results

```
                     Estimates     S.E.  Est./S.E.    Std     StdYX
 F          ON
   INCOME              1.000     0.000     0.000    0.427     0.427
   OCCUP               0.380     0.481     0.790    0.162     0.162
   EDUC                1.640     0.877     1.870    0.700     0.699

 FRIENDS    ON
   F                   0.109     0.045     2.410    0.255     0.256

 Residual Variances
   FRIENDS             0.933     0.057    16.279    0.933     0.935
   F                   0.000     0.000     0.000    0.000     0.000
```

242

Input Excerpts Social Status Formative Indicators, Model 2

```
VARIABLE:   NAMES ARE church members friends income occup educ;
            USEV = church-educ;

MODEL:      fy BY church-friends;
            f BY; ! defining the formative factor
            f ON income@1 occup educ;
            f@0;
            fy ON f;
```

243

Output Excerpts Social Status Formative Indicators, Model 2

Tests Of Model Fit

```
Chi-Square Test of Model Fit
             Value                          12.582
             Degrees of Freedom                  6
             P-Value                        0.0502
```

Model Results

	Estimates	S.E.	Est./S.E.	Std	StdYX
FY BY					
CHURCH	1.000	0.000	0.000	0.466	0.466
MEMBER	1.579	0.235	6.732	0.735	0.736
FRIENDS	0.862	0.143	6.046	0.402	0.402
FY ON					
F	0.108	0.028	3.825	0.508	0.508
F ON					
INCOME	1.000	0.000	0.000	0.457	0.457
OCCUP	0.418	0.276	1.515	0.191	0.191
EDUC	1.438	0.453	3.173	0.658	0.657

244

Output Excerpts Social Status Formative Indicators, Model 2 (Continued)

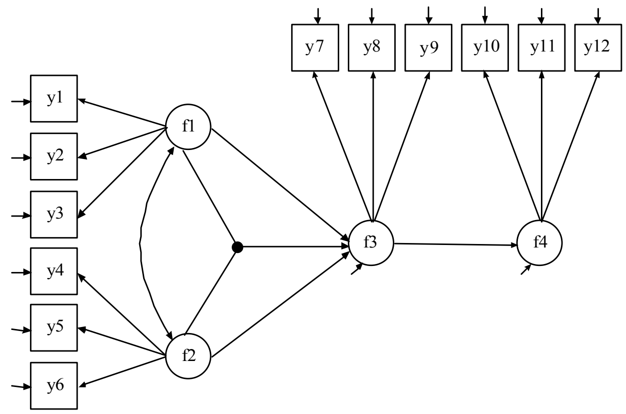
	Estimates	S.E.	Est./S.E.	Std	StdYX
Residual Variances					
CHURCH	0.781	0.057	13.620	0.781	0.783
MEMBER	0.457	0.075	6.092	0.457	0.458
FRIENDS	0.837	0.058	14.528	0.837	0.838
FY	0.161	0.037	4.361	0.742	0.742
F	0.000	0.000	0.000	0.000	0.000

245

Latent Variable Interactions

246

Structural Equation Model With Interaction Between Latent Variables



Klein & Moosbrugger (2000)
Marsh et al. (2004)

Monte Carlo Simulations

Input Monte Carlo Simulation Study For A CFA With Covariates

```
TITLE:       This is an example of a Monte Carlo simulation study
             for a CFA with covariates (MIMIC) with continuous
             factor indicators and patterns of missing data

MONTECARLO:  NAMES ARE y1-y4 x1 x2;
             NOBSERVATIONS = 500;
             NREPS = 500;
             SEED = 4533;
             CUTPOINTS = x2(1);
             PATMISS = y1(.1) y2(.2) y3(.3) y4(1) |
                       y1(1) y2(.1) y3(.2) y4(.3);
             PATPROBS = .4 | .6;

MODEL POPULATION:
             [x1-x2@0];
             x1-x2@1;
             f BY y1@1 y2-y4*1;
             f*.5;
             y1-y4*.5;
             f ON x1*1 x2*.3;
```

249

Input Monte Carlo Simulation Study For A CFA With Covariates (Continued)

```
MODEL:       f BY y1@1 y2-y4*1;
             f*.5;
             y1-y4*.5;
             f ON x1*1 x2*.3;
OUTPUT:      TECH9;
```

250

Output Excerpts Monte Carlo Simulation Study For A CFA With Covariates

Tests Of Model Fit

```
Number of Free Parameters                        14

Chi-Square Test of Model Fit

             Degrees of Freedom                   8

             Mean                             8.297
             Std Dev                          4.122
             Number of successful computations  500
```

251

Output Excerpts Monte Carlo Simulation Study For A CFA With Covariates (Continued)

Proportions		Percentiles	
Expected	Observed	Expected	Observed
0.990	0.996	1.646	2.008
0.980	0.990	2.032	2.597
0.950	0.940	2.733	2.592
0.900	0.896	3.490	3.441
0.800	0.814	4.594	4.711
0.700	0.706	5.527	5.605
0.500	0.542	7.344	7.663
0.300	0.326	9.524	9.993
0.200	0.238	11.030	11.726
0.100	0.120	13.362	14.313
0.050	0.052	15.507	15.575
0.020	0.016	18.168	17.986
0.010	0.006	20.090	19.268

252

Output Excerpts Monte Carlo Simulation Study For A CFA With Covariates (Continued)

Model Results

		ESTIMATES		S.E.	M. S. E.	95%	%Sig
	Population	Average	Std. Dev.	Average		Cover	Coeff
F BY							
Y1	1.000	1.0000	0.0000	0.0000	0.0000	1.000	0.000
Y2	1.000	1.0083	0.0878	0.0847	0.0078	0.932	1.000
Y3	1.000	1.0035	0.0859	0.0801	0.0074	0.938	1.000
Y4	1.000	1.0032	0.0637	0.0654	0.0041	0.954	1.000
F ON							
X1	1.000	0.9990	0.0630	0.0593	0.0040	0.936	1.000
X2	0.300	0.3029	0.1083	0.1056	0.0117	0.954	0.806

MODEL CONSTRAINT

The MODEL CONSTRAINT Command

```
MODEL:
    f1 BY y1
    y2-y3 (lam2-lam3);
    f2 BY y4
    y5-y6 (lam5-lam6);
    f1-f2 (vf1-vf2);
    y1-y6 (ve1-ve6);

MODEL CONSTRAINT:
    NEW(rel2 rel5 stan3 stan6);
    rel2 = lam2**2*vf1/(lam2**2*vf1 + ve2);
    rel5 = lam5**2*vf2/(lam5**2*vf2 + ve5);
    rel5 = rel2;
    stan3 = lam3*sqrt(vf1)/sqrt(lam3**2*vf1 + ve3);
    stan6 = lam6*sqrt(vf2)/sqrt(lam6**2*vf2 + ve6);
```


The MODEL CONSTRAINT Command (Continued)

- New parameters
- 0 = parameter function
- Inequalities
- Constraints involving observed variables

MODEL TEST

- Wald chi-square test of restrictions on parameters
- Restrictions not imposed by the model (unlike MODEL CONSTRAINT)
- Can use labels from the MODEL command and the MODEL CONSTRAINT command

Example: Testing equality of loadings

```
MODEL:
f BY y1-y3* (p1-p3);
f@1;
MODEL TEST:
p2 = p1;
p3 = p1;
```

257

Technical Aspects Of Structural Equation Modeling

General model formulation for *G* groups

$$\boldsymbol{y}_{ig} = \boldsymbol{\nu}_g + \boldsymbol{\Lambda}_g \, \boldsymbol{\eta}_{ig} + \mathbf{K}_g \, \mathbf{x}_{ig} + \boldsymbol{\varepsilon}_{ig}, \tag{26}$$

$$\boldsymbol{\eta}_{ig} = \boldsymbol{\alpha}_g + \mathbf{B}_g \, \boldsymbol{\eta}_{ig} + \boldsymbol{\Gamma}_g \, \mathbf{x}_{ig} + \boldsymbol{\zeta}_{ig}, \tag{27}$$

The covariance matrices $\boldsymbol{\Theta}_g = V(\varepsilon_{ig})$ and $\boldsymbol{\Psi}_g = V(\zeta_{ig})$ are also allowed to vary across the *G* groups.

258

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(To request a Muthén paper, please email bmuthen@ucla.edu and refer to the number in parenthesis.)

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http://gsm.uci.edu/~joelwest/SEM/SEMBooks.html

http://www2.chass.ncsu.edu/garson/pa765/structur.htm is a fairly complete (15) pages general overview of SEM.

Join SEMNET: http://bama.ua.edu/archives/semnet.html