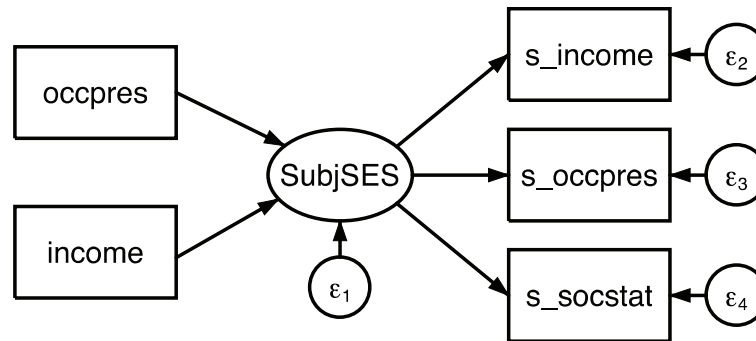


Fitting the MIMIC model

Based on the data referenced above, [Bollen \(1989, 397–399\)](#) fits a MIMIC model, the path diagram of which is



In [Bollen \(1989, 397–399\)](#), he includes paths that he constrains and we do not show. Our model is nonetheless equivalent to the one he shows. In his textbook, Bollen illustrates various ways the same model can be written.

```

. sem (SubjSES -> s_income s_occpres s_socstat) (SubjSES <- income occpres)
Endogenous variables
Measurement:  s_income s_occpres s_socstat
Latent:       SubjSES
Exogenous variables
Observed:    income occpres
Fitting target model:
Iteration 0:  log likelihood = -4252.1834 (not concave)
Iteration 1:  log likelihood = -4022.9057 (not concave)
Iteration 2:  log likelihood = -3994.24
Iteration 3:  log likelihood = -3978.5284 (not concave)
Iteration 4:  log likelihood = -3974.5499
Iteration 5:  log likelihood = -3973.1229
Iteration 6:  log likelihood = -3971.9427
Iteration 7:  log likelihood = -3971.9236
Iteration 8:  log likelihood = -3971.9236
Structural equation model                               Number of obs       =       432
Estimation method = ml
Log likelihood    = -3971.9236
( 1) [s_income]SubjSES = 1

```

	Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
Structural						
SubjSES <- income	.0827327	.0138499	5.97	0.000	.0555874	.109878
occpres	.0046275	.0012464	3.71	0.000	.0021847	.0070704
Measurement						
s_income <- SubjSES _cons	.9612057	1 (constrained) .0794155	12.10	0.000	.8055541	1.116857
s_occpres <- SubjSES _cons	.7301313	.0832913	8.77	0.000	.5668832	.8933793
s_socstat <- SubjSES _cons	.9405104	.0934852	10.06	0.000	.7572827	1.123738
Variance						
e.s_income	.2087534	.0254099			.164446	.2649987
e.s_occpres	.2811856	.0228914			.2397156	.3298296
e.s_socstat	.180714	.0218405			.1425996	.2290157
e.SubjSES	.186012	.027048			.1398838	.2473513

```
LR test of model vs. saturated: chi2(4) = 26.65, Prob > chi2 = 0.0000
```

Notes:

1. In this model, there are three observed variables that record the person's idea of their perceived socioeconomic status (SES). One is the person's general idea of their SES (`s_socstat`); another is based on their income (`s_income`); and the last is based on their occupational prestige (`s_occpres`). Those three variables form the latent variable `SubjSES`.
2. The other two observed variables are the person's income (`income`) and occupation, the latter measured by the two-digit Duncan SEI scores for occupations (`occpres`). These two variables are treated as predictors of `SubjSES`.

3. In the model, (1) is viewed as subjective and (2) is viewed as objective.
4. All variables are statistically significant at the 5% level, but the model versus saturated test suggests that we are not modeling the covariances well.

Evaluating the residuals using estat residuals

Remember that SEM fits covariances and means. Residuals in the SEM sense thus refer to covariances and means. If we are not fitting well, we can examine the residuals.

```
. estat residuals, normalized
```

Residuals of observed variables

Mean residuals

	s_income	s_occpres	s_socstat	income	occpres
raw	0.000	0.000	0.000	0.000	0.000
normalized	0.000	0.000	0.000	0.000	0.000

Covariance residuals

	s_income	s_occpres	s_socstat	income	occpres
s_income	-0.000				
s_occpres	-0.009	0.000			
s_socstat	0.000	0.008	0.000		
income	0.101	-0.079	-0.053	0.000	
occpres	-0.856	1.482	0.049	0.000	0.000

Normalized covariance residuals

	s_income	s_occpres	s_socstat	income	occpres
s_income	-0.000				
s_occpres	-0.425	0.000			
s_socstat	0.008	0.401	0.000		
income	1.362	-1.137	-0.771	0.000	
occpres	-1.221	2.234	0.074	0.000	0.000

Notes:

1. The residuals can be partitioned into two subsets: mean residuals and covariance residuals.
2. The `normalized` option caused the normalized residuals to be displayed.
3. Concerning mean residuals, the raw residuals and the normalized residuals are shown on a separate line of the first table.
4. Concerning covariance residuals, the raw residuals and the normalized residuals are shown in separate tables.
5. Distinguish between normalized residuals and standardized residuals. Both are available from `estat residuals`; if we wanted standardized residuals, we would have specified the `standardized` option instead of or along with `normalized`.
6. Both normalized and standardized residuals attempt to adjust the residuals in the same way. The normalized residuals are always valid, but they do not follow a standard normal distribution. The standardized residuals do follow a standard normal distribution if they can be calculated; otherwise, they will equal missing values. When both can be calculated (equivalent to both being appropriate), the normalized residuals will be a little smaller than the standardized residuals.

7. The normalized covariance residuals between `income` and `s_income` and between `occpres` and `s_occpres` are large.

Performing likelihood-ratio tests using `lrtest`

Thus Bollen suggests adding a direct path from the objective measures to the corresponding subjective measures. We are about to fit the model

```
(SubjSES -> s_income s_occpres s_socstat)  ///
(SubjSES <- income occpres)                ///
(s_income <- income)                        /// <- new
(s_occpres <- occpres)                      //  <- new
```

For no other reason than we want to demonstrate the likelihood-ratio test, we will then use `lrtest` rather than `test` to test the joint significance of the new paths. `lrtest` compares the likelihood values of two fitted models. Thus we will use `lrtest` to compare this new model with the one above. To do that, we must plan ahead and store in memory the currently fit model:

```
. estimates store mimic1
```

Alternatively, we could skip that and calculate the joint significance of the two new paths using a Wald test and the `test` command.

In any case, having stored the current estimates under the name `mimic1`, we can now fit our new model:

```
. sem (SubjSES -> s_income s_occpres s_socstat)
>     (SubjSES <- income occpres)
>     (s_income <- income)
>     (s_occpres <- occpres)

Endogenous variables
Observed:    s_income s_occpres
Measurement: s_socstat
Latent:      SubjSES

Exogenous variables
Observed:    income occpres

Fitting target model:
Iteration 0:  log likelihood = -4267.0974 (not concave)
Iteration 1:  log likelihood = -4022.8637 (not concave)
Iteration 2:  log likelihood = -3977.1937
Iteration 3:  log likelihood = -3962.9248
Iteration 4:  log likelihood = -3961.5382
Iteration 5:  log likelihood = -3960.7634
Iteration 6:  log likelihood = -3960.7112
Iteration 7:  log likelihood = -3960.7111
```

```
Structural equation model          Number of obs   =       432
Estimation method = ml
Log likelihood      = -3960.7111
( 1)  [s_income]SubjSES = 1
```

	Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
Structural						
s_inc~e <- SubjSES	1	(constrained)				
income	.0532426	.0142861	3.73	0.000	.0252423	.081243
_cons	.8825316	.0781684	11.29	0.000	.7293243	1.035739
s_occ~s <-						
SubjSES	.7837824	.1011453	7.75	0.000	.5855412	.9820235
occpres	.0045201	.0013552	3.34	0.001	.0018641	.0071762
_cons	1.06586	.0696057	15.31	0.000	.9294357	1.202285
SubjSES <-						
income	.0538023	.0129157	4.17	0.000	.0284881	.0791166
occpres	.0034324	.0011217	3.06	0.002	.0012339	.0056309
Measurement						
s_soc~t <- SubjSES	1.195539	.158271	7.55	0.000	.8853336	1.505745
_cons	1.07922	.0783231	13.78	0.000	.9257099	1.232731
Variance						
e.s_income	.22927	.0248903			.1853267	.2836327
e.s_occ~s	.2773785	.0223972			.2367782	.3249405
e.s_soc~t	.1459008	.0282278			.0998559	.2131777
e.SubjSES	.1480268	.0278376			.1023919	.2140007

```
LR test of model vs. saturated: chi2(2) = 4.22, Prob > chi2 = 0.1211
```

Now we can perform the likelihood-ratio test:

```
. lrtest mimic1 .
Likelihood-ratio test          LR chi2(2) = 22.42
(Assumption: mimic1 nested in .) Prob > chi2 = 0.0000
```

Notes:

1. The syntax of `lrtest` is `lrtest modelname1 modelname2`. We specified the first model name as `mimic1`, the model we previously stored. We specified the second model name as `period (.)`, meaning the model most recently fit. The order in which we specify the names is irrelevant.
2. We find the two added paths to be whoppingly significant.

Also see

- [SEM] [sem](#) — Structural equation model estimation command
- [SEM] [estat residuals](#) — Display mean and covariance residuals
- [SEM] [lrtest](#) — Likelihood-ratio test of linear hypothesis

Title

example 11 — estat framework

Description

To demonstrate `estat framework`, which displays results in Bentler–Weeks form, we continue from where [\[SEM\] example 10](#) left off:

```
. use http://www.stata-press.com/data/r12/sem_mimic1
. ssd describe
. notes
. sem (SubjSES -> s_income s_occpres s_socstat)   ///
      (SubjSES <- income occpres)
. estat residuals, normalized
. estimates store mimic1
. sem (SubjSES -> s_income s_occpres s_socstat)   ///
      (SubjSES <- income occpres)               ///
      (s_income <- income)                       ///
      (s_occpres <- occpres)
. lrtest mimic1 .
```

See *Structural models 4: MIMIC* in [\[SEM\] intro 4](#) for background.

Remarks

If you prefer to see SEM results reported in Bentler–Weeks form, type `estat framework` after estimating using `sem`. Many people find Bentler–Weeks form helpful in understanding how the model is fit.

[\[SEM\] example 10](#) ended by fitting

```
. sem (SubjSES -> s_income s_occpres s_socstat)   ///
      (SubjSES <- income occpres)               ///
      (s_income <- income)                       ///
      (s_occpres <- occpres)
```

In Bentler–Weeks form, the output appears as

```
. estat framework, fitted
```

Endogenous variables on endogenous variables

Beta	observed s_income	s_occpres	s_socstat	latent SubjSES
observed				
s_income	0	0	0	1
s_occpres	0	0	0	.7837824
s_socstat	0	0	0	1.195539
latent				
SubjSES	0	0	0	0