Example 17 — Correlated uniqueness model

Description

To demonstrate a correlated uniqueness model, we use the following summary statistics data:

```
. use https://www.stata-press.com/data/r16/sem_cu1
(Correlated uniqueness)
. ssd describe
obs: 500   vars: 9   18 Jan 2019 09:34
(_dta has notes)

variable name      variable label
par_i              self-report inventory for paranoid
szt_i              self-report inventory for schizotypal
szd_i              self-report inventory for schizoid
par_c              clinical interview rating for paranoid
szt_c              clinical interview rating for schizotypal
szd_c              clinical interview rating for schizoid
par_o              observer rating for paranoid
szt_o              observer rating for schizotypal
szd_o              observer rating for schizoid

. notes
_dta:
2. Summary statistics represent a sample of 500 patients who were evaluated for three personality disorders using three different methods.
3. The personality disorders include paranoid, schizotypal, and schizoid.
4. The methods of evaluation include a self-report inventory, ratings from a clinical interview, and observational ratings.

See Correlated uniqueness model in [SEM] Intro 5 for background.
Fitting the model

We fit the following model:

\[ \begin{align*}
&\text{. sem (Par -> par_i par_c par_o)} \\
&\quad > (Szt -> szt_i szt_c szt_o) \\
&\quad > (Szd -> szd_i szd_c szd_o), \\
&\quad \text{covstr(e.par_i e.szt_i e.szd_i, unstructured)} \\
&\quad \text{covstr(e.par_c e.szt_c e.szd_c, unstructured)} \\
&\quad \text{covstr(e.par_o e.szt_o e.szd_o, unstructured)} \\
&\quad \text{standardized}
\end{align*} \]

Endogenous variables

Measurement: par_i par_c par_o szt_i szt_c szt_o szd_i szd_c szd_o

Exogenous variables

Latent: Par Szt Szd

Fitting target model:

Iteration 0: log likelihood = -10210.31 (not concave)
Iteration 1: log likelihood = -10040.188 (not concave)
Iteration 2: log likelihood = -9971.4015
Iteration 3: log likelihood = -9918.0037
Iteration 4: log likelihood = -9883.6368
Iteration 5: log likelihood = -9880.0242
Iteration 6: log likelihood = -9879.9961
Iteration 7: log likelihood = -9879.9961
Example 17 — Correlated uniqueness model

Number of obs = 500
Estimation method = ml
Log likelihood = -9879.9961

( 1) [par_i]Par = 1
( 2) [szt_i]Szt = 1
( 3) [szd_i]Szd = 1

<table>
<thead>
<tr>
<th>Standardized</th>
<th>QIM</th>
<th>GIM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>Std. Err.</td>
</tr>
<tr>
<td>Measurement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>par_i &lt;- Par</td>
<td>.7119709</td>
<td>.0261858</td>
</tr>
<tr>
<td>par_c &lt;- Par</td>
<td>.8410183</td>
<td>.0242205</td>
</tr>
<tr>
<td>par_o &lt;- Par</td>
<td>.7876062</td>
<td>.0237685</td>
</tr>
<tr>
<td>szt_i &lt;- Szt</td>
<td>.7880887</td>
<td>.0202704</td>
</tr>
<tr>
<td>szt_c &lt;- Szt</td>
<td>.7675732</td>
<td>.0244004</td>
</tr>
<tr>
<td>szt_o &lt;- Szt</td>
<td>.8431662</td>
<td>.0181632</td>
</tr>
<tr>
<td>szd_i &lt;- Szt</td>
<td>.7692321</td>
<td>.0196626</td>
</tr>
<tr>
<td>szd_c &lt;- Szt</td>
<td>.8604596</td>
<td>.0179455</td>
</tr>
<tr>
<td>szd_o &lt;- Szt</td>
<td>.8715597</td>
<td>.0155875</td>
</tr>
<tr>
<td>var(e.par_i)</td>
<td>.4930975</td>
<td>.0372871</td>
</tr>
<tr>
<td>var(e.par_c)</td>
<td>.2926882</td>
<td>.0407398</td>
</tr>
<tr>
<td>var(e.par_o)</td>
<td>.3796764</td>
<td>.0374404</td>
</tr>
<tr>
<td>var(e.szt_i)</td>
<td>.3789163</td>
<td>.0319498</td>
</tr>
<tr>
<td>var(e.szt_c)</td>
<td>.4108313</td>
<td>.0374582</td>
</tr>
<tr>
<td>var(e.szt_o)</td>
<td>.2890708</td>
<td>.0306291</td>
</tr>
<tr>
<td>var(e.szd_i)</td>
<td>.4082822</td>
<td>.0302501</td>
</tr>
<tr>
<td>var(e.szd_c)</td>
<td>.2596093</td>
<td>.0308827</td>
</tr>
<tr>
<td>var(e.szd_o)</td>
<td>.2403837</td>
<td>.027171</td>
</tr>
<tr>
<td>var(Par)</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>var(Szt)</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>var(Szd)</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
Example 17 — Correlated uniqueness model

<table>
<thead>
<tr>
<th>cov</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>e.par_i, e.szt_i</td>
<td>.2166732</td>
<td>.0535966</td>
<td>4.04</td>
<td>0.000</td>
<td>.1116258</td>
<td>.3217207</td>
</tr>
<tr>
<td>e.par_i, e.szd_i</td>
<td>.4411039</td>
<td>.0451782</td>
<td>9.76</td>
<td>0.000</td>
<td>.3525563</td>
<td>.5296515</td>
</tr>
<tr>
<td>e.par_c, e.szt_c</td>
<td>-.1074802</td>
<td>.0691107</td>
<td>-1.56</td>
<td>0.120</td>
<td>-.2429348</td>
<td>.0279743</td>
</tr>
<tr>
<td>e.par_c, e.szd_c</td>
<td>-.2646125</td>
<td>.0836965</td>
<td>-3.16</td>
<td>0.002</td>
<td>-.4286546</td>
<td>-.1005705</td>
</tr>
<tr>
<td>e.par_o, e.szt_o</td>
<td>.4132457</td>
<td>.0571588</td>
<td>7.23</td>
<td>0.000</td>
<td>.3012165</td>
<td>.5252749</td>
</tr>
<tr>
<td>e.par_o, e.szd_o</td>
<td>.3684402</td>
<td>.0587572</td>
<td>6.27</td>
<td>0.000</td>
<td>.2532781</td>
<td>.4836022</td>
</tr>
<tr>
<td>e.szt_i, e.szd_i</td>
<td>.7456394</td>
<td>.0351079</td>
<td>21.24</td>
<td>0.000</td>
<td>.6768292</td>
<td>.8144962</td>
</tr>
<tr>
<td>e.szt_c, e.szd_c</td>
<td>-.3296552</td>
<td>.0720069</td>
<td>-4.58</td>
<td>0.000</td>
<td>-.4707861</td>
<td>-.1885244</td>
</tr>
<tr>
<td>e.szt_o, e.szd_o</td>
<td>.4781276</td>
<td>.0588923</td>
<td>8.12</td>
<td>0.000</td>
<td>.3627009</td>
<td>.5935544</td>
</tr>
<tr>
<td>(Par, Szt)</td>
<td>.3806759</td>
<td>.0456989</td>
<td>8.33</td>
<td>0.000</td>
<td>.2911095</td>
<td>.4702422</td>
</tr>
<tr>
<td>(Par, Szd)</td>
<td>.3590146</td>
<td>.0456235</td>
<td>7.87</td>
<td>0.000</td>
<td>.2695941</td>
<td>.4484351</td>
</tr>
<tr>
<td>(Szt, Szd)</td>
<td>.3103837</td>
<td>.0466126</td>
<td>6.66</td>
<td>0.000</td>
<td>.2190246</td>
<td>.4017428</td>
</tr>
</tbody>
</table>

LR test of model vs. saturated: chi2(15) = 14.37, Prob > chi2 = 0.4976

Notes:

1. We use the correlated uniqueness model fit above to analyze a multitrait–multimethod (MTMM) matrix. The MTMM matrix was developed by Campbell and Fiske (1959) to evaluate construct validity of measures. Each trait is measured using different methods, and the correlation matrix produced is used to evaluate whether measures that are related in theory are related in fact (convergent validity) and whether measures that are not intended to be related are not related in fact (discriminant validity).

In this example, the traits are the latent variables Par, Szt, and Szd.

The observed variables are the method–trait combinations.

The observed traits are the personality disorders paranoid (par), schotypal (szt), and schizoid (szd). The methods used to measure them are self-report (_i), clinical interview (_c), and observer rating (_o). Thus variable par_i is paranoid (par) measured by self-report (_i).

2. Note our use of the covstructure() option, which we abbreviated to covstr(). We used this option instead of cov() to save typing; see Correlated uniqueness model in [SEM] Intro 5.

3. Large values of the factor loadings (path coefficients) indicate convergent validity.

4. Small correlations between latent variables indicate discriminant validity.

Fitting the model with the Builder

Use the diagram above for reference.

There are many ways to draw this diagram. This one produces the cleanest diagram most easily.

1. Open the dataset.

In the Command window, type

```
   . use https://www.stata-press.com/data/r16/sem_cu1
```
2. Open a new Builder diagram.
   Select menu item **Statistics > SEM (structural equation modeling) > Model building and estimation.**

3. Change the size of the observed variables’ rectangles.
   a. In the SEM Builder menu, select **Settings > Variables > All observed...**
   b. In the resulting dialog box, change the first size to .44 and click on **OK.**

4. Create the nine measurement variables.
   Select the Add observed variables set tool, ◯◯, and then click in the far left of the diagram, about one-third of the way up from the bottom.
   In the resulting dialog box,
   a. select the **Select variables** radio button (it may already be selected);
   b. use the **Variables** control to select the nine variables in this order: par_i, szt_i, szd_i, par_c, szt_c, szd_c, par_o, szt_o, and szd_o;
   c. select **Horizontal** in the **Orientation** control;
   d. click on **OK.**
   If you wish, move the set of variables by clicking on any variable and dragging it.
   Be sure you select the observed variables in the order indicated above; otherwise, the instructions below for creating covariances among the errors will not be correct.

5. Create the set of three latent variables.
   Select the Add latent variables set tool, ◯◯, and then click above the szt_i rectangle, about one-third of the way down from the top of the diagram.
   In the resulting dialog box,
   a. select the **Select variables** radio button (it may already be selected);
   b. type the three latent variable names Par, Szt, and Szd into the **Variables** control;
   c. select **Horizontal** in the **Orientation** control;
   d. select the **Distances** tab;
   e. select 1 (inch) from the **Distance between variables** control;
   f. click on **OK.**
   If you wish, move the set of variables by clicking on any variable and dragging it.
   We could have forgone specifying the distances between variables and simply dragged each variable where we wished after it was created.

6. Create the factor-loading paths.
   a. Select the Add path tool, —.
   b. Click in the bottom of the Par oval (it will highlight when you hover over it), and drag a path to the top of the par_i rectangle (it will highlight when you can release to connect the path).
c. Continuing with the tool, create the following paths by clicking first in the bottom of the latent variable and dragging it to the top of the observed (measurement) variable:

\[
\begin{align*}
Szt & \rightarrow szt_i \\
Szd & \rightarrow szd_i \\
Par & \rightarrow par_c \\
Szt & \rightarrow szt_c \\
Szd & \rightarrow szd_c \\
Par & \rightarrow par_o \\
Szt & \rightarrow szt_o \\
Szd & \rightarrow szd_o
\end{align*}
\]

7. Clean up the direction of the errors.
   We want all the errors to be below the measurement variables.
   a. Choose the Select tool,.
   b. Click on the rectangle of any measurement variable whose associated error is not below it.
   c. Click on one of the Error rotation buttons, ↡ ↢, in the Contextual Toolbar until the error is below the measurement variable.

Repeat this for all errors that are not below the measurement variables.

8. Correlate the errors within the self-report, clinical interview, and observer rating groups.
   a. Select the Add covariance tool, ⊲.
   b. Click in the \( \epsilon_2 \) circle (it will highlight when you hover over it), and drag a covariance to the \( \epsilon_1 \) circle (it will highlight when you can release to connect the covariance).
   c. Continue with the Add covariance tool, ⊲, to create eight more covariances by clicking the first-listed error and dragging it to the second-listed error.

\[
\begin{align*}
\epsilon_3 & \rightarrow \epsilon_2 \\
\epsilon_3 & \rightarrow \epsilon_1 \\
\epsilon_5 & \rightarrow \epsilon_4 \\
\epsilon_6 & \rightarrow \epsilon_5 \\
\epsilon_6 & \rightarrow \epsilon_4 \\
\epsilon_8 & \rightarrow \epsilon_7 \\
\epsilon_9 & \rightarrow \epsilon_8 \\
\epsilon_9 & \rightarrow \epsilon_7
\end{align*}
\]

The order in which we create the covariances is unimportant. We dragged each covariance from right to left because the bow of the covariance is outward when we drag in a clockwise direction and inward when we drag in a counterclockwise direction. Had we connected the opposite way, we would have needed to use the Contextual Toolbar to mirror the bow of the covariances.

9. Correlate the latent factors.
   a. Select the Add covariance tool, ⊲.
   b. Click in the Par oval and drag a covariance to the Szt oval.
   c. Click in the Szt oval and drag a covariance to the Szd oval.
   d. Click in the Par oval and drag a covariance to the Szd oval.
10. Clean up.

If you do not like where a covariance has been connected to its variable, use the Select tool, , to click on the covariance, and then simply click on where it connects to an oval and drag the endpoint. You can also change the bow of the covariance by dragging the control point that extends from one end of the selected covariance.

11. Estimate.

Click on the Estimate button, , in the Standard Toolbar, and then click on OK in the resulting SEM estimation options dialog box.

12. Show standardized estimates.

From the SEM Builder menu, select View > Standardized estimates.

Reference


Also see

[SEM] sem — Structural equation model estimation command

[SEM] sem and gsem option covstructure() — Specifying covariance restrictions