Example 17 — Correlated uniqueness model

Description Remarks and examples Reference Also see

Description

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

```
. use https://www.stata-press.com/data/r17/sem_cu1
(Correlated uniqueness)

. ssd describe

  Summary statistics data from
  https://www.stata-press.com/data/r17/sem_cu1.dta
  Observations:             500          Correlated uniqueness
     Variables:               9          18 Jan 2021 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 schizoty..
  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:
  1.  Summary statistic data for multitrait-multimethod matrix (a specific kind
      of correlation matrix) and standard deviations from Brown, T. A. 2015.
      Confirmatory Factor Analysis for Applied Research. 2nd ed. New York:
      Guilford Press.
  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.

Remarks and examples

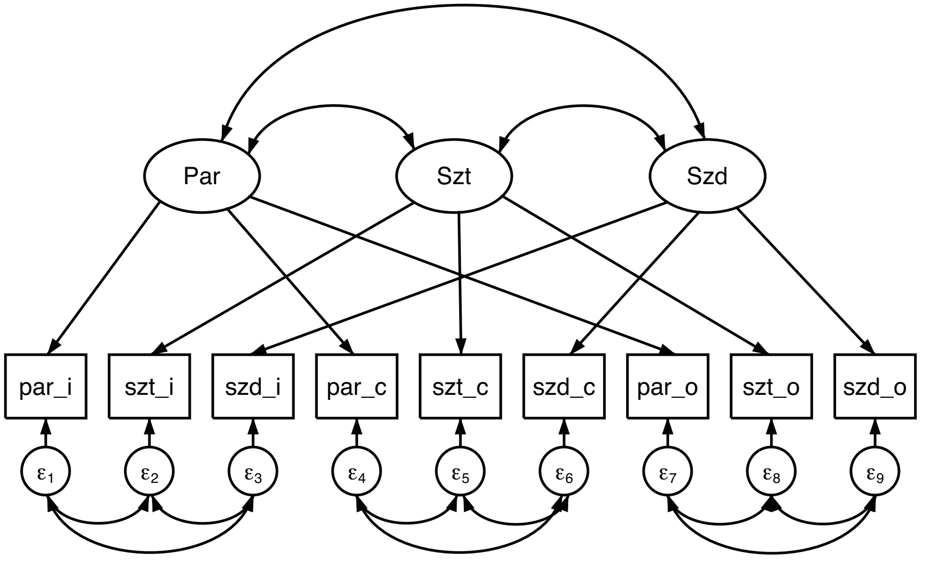
stata.com

Remarks are presented under the following headings:

Fitting the model
Fitting the model with the Builder

Fitting the model

We fit the following model:




```
. sem (Par -> par_i par_c par_o)
>     (Szt -> szt_i szt_c szt_o)
>     (Szd -> szd_i szd_c szd_o),
>               covstr(e.par_i e.szt_i e.szd_i, unstructured)
>               covstr(e.par_c e.szt_c e.szd_c, unstructured)
>               covstr(e.par_o e.szt_o e.szd_o, unstructured)
>               standardized
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

Structural equation 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

                                 OIM
 Standardized   Coefficient  std. err.      z    P>|z|     [95% conf. interval]

Measurement
  par_i
         Par      .7119709   .0261858    27.19   0.000     .6606476    .7632941

  par_c
         Par      .8410183   .0242205    34.72   0.000     .7935469    .8884897

  par_o
         Par      .7876062   .0237685    33.14   0.000     .7410209    .8341916

  szt_i
         Szt      .7880887   .0202704    38.88   0.000     .7483594    .8278179

  szt_c
         Szt      .7675732   .0244004    31.46   0.000     .7197493    .8153972

  szt_o
         Szt      .8431662   .0181632    46.42   0.000      .807567    .8787653

  szd_i
         Szd      .7692321   .0196626    39.12   0.000     .7306942      .80777

  szd_c
         Szd      .8604596   .0179455    47.95   0.000     .8252871    .8956321

  szd_o
         Szd      .8715597   .0155875    55.91   0.000     .8410086    .9021107

 var(e.par_i)     .4930975   .0372871                      .4251739    .5718722
 var(e.par_c)     .2926882   .0407398                      .2228049    .3844905
 var(e.par_o)     .3796764   .0374404                      .3129503    .4606295
 var(e.szt_i)     .3789163   .0319498                      .3211966    .4470082
 var(e.szt_c)     .4108313   .0374582                      .3436006    .4912169
 var(e.szt_o)     .2890708   .0306291                      .2348623    .3557912
 var(e.szd_i)      .408282   .0302501                      .3530966    .4720922
 var(e.szd_c)     .2596093   .0308827                      .2056187    .3277766
 var(e.szd_o)     .2403837    .027171                       .192616    .2999976
     var(Par)            1          .                             .           .
     var(Szt)            1          .                             .           .
     var(Szd)            1          .                             .           .
```

```
──────────────┬──────────────────────────────────────────────────────────────────
cov(e.par_i,  │
     e.szt_i) │   .2166732   .0535966     4.04   0.000     .1116258    .3217207
cov(e.par_i,  │
     e.szd_i) │   .4411039   .0451782     9.76   0.000     .3525563    .5296515
cov(e.par_c,  │
     e.szt_c) │  -.1074802   .0691107    -1.56   0.120    -.2429348    .0279743
cov(e.par_c,  │
     e.szd_c) │  -.2646125   .0836965    -3.16   0.002    -.4286546   -.1005705
cov(e.par_o,  │
     e.szt_o) │   .4132457   .0571588     7.23   0.000     .3012165    .5252749
cov(e.par_o,  │
     e.szd_o) │   .3684402   .0587572     6.27   0.000     .2532781    .4836022
cov(e.szt_i,  │
     e.szd_i) │   .7456394   .0351079    21.24   0.000     .6768292    .8144496
cov(e.szt_c,  │
     e.szd_c) │  -.3296552   .0720069    -4.58   0.000    -.4707861   -.1885244
cov(e.szt_o,  │
     e.szd_o) │   .4781276   .0588923     8.12   0.000     .3627009    .5935544
 cov(Par,Szt) │   .3806759    .045698     8.33   0.000     .2911095    .4702422
 cov(Par,Szd) │   .3590146   .0456235     7.87   0.000     .2695941    .4484351
 cov(Szt,Szd) │   .3103837   .0466126     6.66   0.000     .2190246    .4017428
──────────────┴──────────────────────────────────────────────────────────────────
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/r17/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:

```
Szt -> szt_i
Szd -> szd_i
Par -> par_c
Szt -> szt_c
Szd -> szd_c
Par -> par_o
Szt -> szt_o
Szd -> szd_o
```

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 ϵ_2 circle (it will highlight when you hover over it), and drag a covariance to the ϵ_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.

   ϵ_3 -> ϵ_2
   ϵ_3 -> ϵ_1
   ϵ_5 -> ϵ_4
   ϵ_6 -> ϵ_5
   ϵ_6 -> ϵ_4
   ϵ_8 -> ϵ_7
   ϵ_9 -> ϵ_8
   ϵ_9 -> ϵ_7

   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

Campbell, D. T., and D. W. Fiske. 1959. Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin* 56: 81–105. http://doi.org/10.1037/h0046016.

Also see

[SEM] **sem** — Structural equation model estimation command

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