example 42g — One- and two-level mediation models (multilevel)

Description

To demonstrate linear mediation models, we use the following data:

```
. use http://www.stata-press.com/data/r13/gsem_multmed
(Fictional job-performance data)
. summarize

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>branch</td>
<td>1500</td>
<td>38</td>
<td>21.65593</td>
<td>1</td>
<td>75</td>
</tr>
<tr>
<td>support</td>
<td>1500</td>
<td>0.0084667</td>
<td>0.5058316</td>
<td>-1.6</td>
<td>1.8</td>
</tr>
<tr>
<td>satis</td>
<td>1500</td>
<td>0.0212</td>
<td>0.6087235</td>
<td>-1.6</td>
<td>2</td>
</tr>
<tr>
<td>perform</td>
<td>1500</td>
<td>5.005317</td>
<td>0.8949845</td>
<td>2.35022</td>
<td>8.084294</td>
</tr>
</tbody>
</table>
```

`. notes
_dta:
1. Fictional data on job performance, job satisfaction, and perceived support from managers for 1,500 sales employees of a large department store in 75 locations.
2. Variable support is average of Likert-scale questions, each question scored from -2 to 2.
3. Variable satis is average of Likert-scale questions, each question scored from -2 to 2.
4. Variable perform is job performance measured on continuous scale.

See Structural models 1: Linear regression and Multilevel mixed-effects models in [SEM] intro 5 for background.

Remarks and examples

Remarks are presented under the following headings:

- One-level model with sem
- One-level model with gsem
- Two-level model with gsem
- Fitting the models with the Builder

One-level model with sem

You can fit single-level mediation models with sem or gsem. You will be better off using sem because then you can use estat teffects afterward to compute indirect and total effects.
The model we wish to fit is the simplest form of a mediation model, namely,

\[
\begin{align*}
\text{support} & \rightarrow \varepsilon_1 \\
\text{satis} & \rightarrow \varepsilon_2 \\
\text{perform} & \rightarrow \varepsilon_3
\end{align*}
\]

We are interested in the effect of managerial support on job performance, but we suspect a portion of the effect might be mediated through job satisfaction. In traditional mediation analysis, the model would be fit by a series of linear regression models as described in Baron and Kenny (1986). That approach is sufficient because the errors are not correlated. The advantage of using structural equation modeling is that you can fit a single model and estimate the indirect and total effects, and you can embed the simple mediation model in a larger model and even use latent variables to measure any piece of the mediation model.

To fit this model with the command syntax, we type

```
. sem (perform <- satis support) (satis <- support)
```

Endogenous variables

| Observed: | perform | satis |

Exogenous variables

| Observed: | support |

Fitting target model:

| Iteration 0: | log likelihood = -3779.9224 |
| Iteration 1: | log likelihood = -3779.9224 |

Structural equation model

| Estimation method | ml |
| Log likelihood | -3779.9224 |


<table>
<thead>
<tr>
<th></th>
<th>QIM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
</tr>
<tr>
<td><strong>Structural</strong></td>
<td></td>
</tr>
<tr>
<td>perform &lt;-</td>
<td></td>
</tr>
<tr>
<td>satis</td>
<td>.8984401</td>
</tr>
<tr>
<td>support</td>
<td>.6161077</td>
</tr>
<tr>
<td>_cons</td>
<td>4.981054</td>
</tr>
<tr>
<td>satis &lt;-</td>
<td></td>
</tr>
<tr>
<td>support</td>
<td>.2288945</td>
</tr>
<tr>
<td>_cons</td>
<td>.019262</td>
</tr>
<tr>
<td>var(e.perform)</td>
<td>.3397087</td>
</tr>
<tr>
<td>var(e.satis)</td>
<td>.3569007</td>
</tr>
</tbody>
</table>

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

1. The direct effect of managerial support on job performance is measured by `perform <- support` and is estimated to be 0.6161. The effect is small albeit highly statistically significant. The standard deviations of performance and support are 0.89 and 0.51. A one standard deviation increase in support improves performance by a third of a standard deviation.

2. The direct effect of job satisfaction on job performance is measured by `perform <- satis` and is estimated to be 0.8984. That also is a moderate effect, practically speaking, and is highly statistically significant.

3. The effect of managerial support on job satisfaction is measured by `satis <- support` and is practically small but statistically significant.

4. What is the total effect of managerial support on performance? It is the direct effect (0.6161) plus the indirect effect of support on satisfaction on performance $(0.2289 \times 0.8984 = 0.2056)$, meaning the total effect is 0.8217. It would be desirable to put a standard error on that, but that’s more work.

We can use `estat teffects` after estimation to obtain the total effect and its standard error:

```
. estat teffects
```

**Direct effects**

| OIM              | Coef. | Std. Err. | z      | P>|z|  | [95% Conf. Interval] |
|------------------|-------|-----------|--------|------|---------------------|
| Structural       |       |           |        |      |                     |
| `perform <- satis` | .8984401 | .0251903  | 35.67  | 0.000 | .849068 .9478123    |
| `support`        | .6161077 | .0303143  | 20.32  | 0.000 | .5566927 .6755227   |
| `satis <- support` | .2288945 | .0305047  | 7.50   | 0.000 | .1691064 .2886826   |

**Indirect effects**

| OIM              | Coef. | Std. Err. | z      | P>|z|  | [95% Conf. Interval] |
|------------------|-------|-----------|--------|------|---------------------|
| Structural       |       |           |        |      |                     |
| `perform <- satis` | 0 (no path) |  |        |      |                     |
| `support`        | .205648 | .0280066  | 7.34   | 0.000 | .150756 .26054     |
| `satis <- support` | 0 (no path) |  |        |      |                     |

**Total effects**

| OIM              | Coef. | Std. Err. | z      | P>|z|  | [95% Conf. Interval] |
|------------------|-------|-----------|--------|------|---------------------|
| Structural       |       |           |        |      |                     |
| `perform <- satis` | .8984401 | .0251903  | 35.67  | 0.000 | .849068 .9478123    |
| `support`        | .8217557 | .0404579  | 20.31  | 0.000 | .7424597 .9010516   |
| `satis <- support` | .2288945 | .0305047  | 7.50   | 0.000 | .1691064 .2886826   |
One-level model with gsem

We can fit the same model with `gsem`. The command is the same except that we substitute `gsem` for `sem`, and results are identical:

```
gsem (perform <- satis support) (satis <- support)
```

**Iteration 0:** log likelihood = -2674.3421  
**Iteration 1:** log likelihood = -2674.3421

Generalized structural equation model  Number of obs = 1500  
Log likelihood = -2674.3421

|               | Coef. | Std. Err. | z    | P>|z|  | [95% Conf. Interval] |
|---------------|-------|-----------|------|------|---------------------|
| perform <- satis | 0.8984401 | 0.0251903 | 35.67 | 0.000 | 0.849068 - 0.9478123 |
| support       | 0.6161077 | 0.0303143 | 20.32 | 0.000 | 0.5566927 - 0.6755227 |
| _cons         | 4.981054  | 0.0150589 | 330.77| 0.000 | 4.951539 - 5.010569  |
| satis <- support | 0.2288945 | 0.0305047 | 7.50  | 0.000 | 0.1691064 - 0.2886826 |
| _cons         | 0.019262  | 0.0154273 | 1.25  | 0.212 | -0.0109749 - 0.0494989 |
| var(e.perf~m) | 0.3397087 | 0.0124044 | 31.62461 | 0.364912 |
| var(e.satis)  | 0.3569007 | 0.0130322 | 332.507 | 0.3833795 |

After gsem, however, we cannot use `estat teffects`:

```
estat teffects
invalid subcommand teffects
r(321);
```

We can, however, calculate the indirect and total effects for ourselves and obtain the standard error by using `nlcom`. Referring back to note 4 of the previous section, the formula for the indirect effect and total effects are

\[
\text{indirect effect} = \beta_1 \beta_4 \\
\text{total effect} = \beta_2 + \beta_1 \beta_4
\]

where

\[
\beta_1 = \text{path coefficient for perform } \leftarrow \text{ satis} \\
\beta_4 = \text{path coefficient for satis } \leftarrow \text{ support} \\
\beta_2 = \text{path coefficient for perform } \leftarrow \text{ support}
\]

It turns out that we can access the coefficients by typing

```
\beta_1 = _b[perform:satis] \\
\beta_4 = _b[satis:support] \\
\beta_2 = _b[perform:support]
```

which is most easily revealed by typing

```
gsem, coeflegend
(output omitted)
```
Thus we can obtain the indirect effect by typing
\[
\text{nlcom} \quad \_b\{\text{perform:satis}\} \ast \_b\{\text{satis:support}\}
\]

\[
\_nl\_1: \quad \_b\{\text{perform:satis}\} \ast \_b\{\text{satis:support}\}
\]

| Coef. | Std. Err. | z   | P>|z| | [95% Conf. Interval] |
|-------|-----------|-----|------|---------------------|
| \_nl\_1 | .205648   | .0280066 | 7.34 | 0.000 | .150756 .26054 |

and we can obtain the total effect by typing
\[
\text{nlcom} \quad \_b\{\text{perform:support}\} + \_b\{\text{perform:satis}\} \ast \_b\{\text{satis:support}\}
\]

\[
\_nl\_1: \quad \_b\{\text{perform:support}\} + \_b\{\text{perform:satis}\} \ast \_b\{\text{satis:support}\}
\]

| Coef. | Std. Err. | z   | P>|z| | [95% Conf. Interval] |
|-------|-----------|-----|------|---------------------|
| \_nl\_1 | .8217557 | .0404579 | 20.31 | 0.000 | .7424597 .9010516 |

**Two-level model with gsem**

It may be easier to use `sem` rather than `gsem` for fitting single-level models, but if you want to fit multilevel models, you must use `gsem`. A variation on the model we just fit is

![Diagram of two-level mediation model with random intercepts at the branch level.](image)

In this model, we include a random intercept in each equation at the branch (individual store) level. The model above is one of many variations on two-level mediation models; see Krull and MacKinnon (2001) for an introduction to multilevel mediation models, and see Preacher, Zyphur, and Zhang (2010) for a discussion of fitting these models with structural equation modeling.
To fit this model with the command syntax, we type

```
.gsem (perform <- satis support M1[branch]) (satis <- support M2[branch]),
> cov(M1[branch]*M2[branch]@0)
```

Fitting fixed-effects model:
Iteration 0: log likelihood = -2674.3421
Iteration 1: log likelihood = -2674.3421

Refining starting values:
Grid node 0: log likelihood = -2132.1613

Fitting full model:
Iteration 0: log likelihood = -2132.1613 (not concave)
Iteration 1: log likelihood = -1801.3155
Iteration 2: log likelihood = -1769.6421
Iteration 3: log likelihood = -1705.1282
Iteration 4: log likelihood = -1703.746
Iteration 5: log likelihood = -1703.7141
Iteration 6: log likelihood = -1703.714

Generalized structural equation model

<table>
<thead>
<tr>
<th>Number of obs</th>
<th>Number of obs</th>
<th>Number of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1500</td>
<td>-1703.714</td>
<td>(1) [perform]M1[branch] = 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) [satis]M2[branch] = 1</td>
</tr>
</tbody>
</table>

|             | Coef. | Std. Err. | z     | P>|z|  | [95% Conf. Interval] |
|-------------|-------|-----------|-------|------|---------------------|
| perform <-  |       |           |       |      |                     |
| satis       | .6042646 | .0336398  | 17.96 | 0.000| .5383313 .6701968  |
| support     | .6981525 | .0250432  | 27.88 | 0.000| .6490687 .7472364  |
| M1[branch]  | 1     | (constrained) |
| _cons       | 4.986596 | .0489465  | 101.88| 0.000| 4.890663 5.082529 |
| satis <-    |       |           |       |      |                     |
| support     | .2692633 | .0179649  | 14.99 | 0.000| .2340528 .3044739 |
| M2[branch]  | 1     | (constrained) |
| _cons       | .0189202 | .0570868  | 0.33  | 0.740| -.0929678 .1308083 |
| var(        |       |           |       |      |                     |
| M1[branch]) | .1695962 | .0302866  | .119511 | .2406713 |
| var(        |       |           |       |      |                     |
| M2[branch]) | .2384738 | .0399154  | .1717781 | .3310652 |
| var(e.perf~m) | .201053 | .0075451  | .1867957 | .2163985 |
| var(e.satis)| .1188436 | .0044523  | .1104299 | .1278983 |

Notes:

1. In One-level model with sem above, we measured the direct effects on job performance of job satisfaction and managerial support as 0.8984 and 0.6161. Now the direct effects are 0.6043 and 0.6982.

2. We can calculate the indirect and total effects just as we did in the previous section, which we will do below. We mentioned earlier that there are other variations of two-level mediation models, and how you calculate total effects depends on the model chosen.
In this case, the indirect effect is

\[ \text{nlcom} \, _b[\text{perform:satis}] * _b[\text{satis:support}] \]

and the total effect is

\[ \text{nlcom} \, _b[\text{perform:support}] + _b[\text{perform:satis}] * _b[\text{satis:support}] \]

Fitting the models with the Builder

Use the diagram in *One-level model with sem* above for reference.

1. Open the dataset.
   In the Command window, type
   \[ \text{use http://www.stata-press.com/data/r13/gsem_multmed} \]

2. Open a new Builder diagram.
   Select menu item *Statistics > SEM (structural equation modeling) > Model building and estimation*.

3. Create a regression component for the *perform* outcome.
   Select the Add Regression Component tool, and then click in the center of the diagram.
   In the resulting dialog box,
   a. select *perform* in the *Dependent variable* control;
   b. select *support* with the *Independent variables* control;
   c. select *Left* in the *Independent variables’ direction* control;
   d. click on OK.
   e. Use the Select tool, to select only the *perform* rectangle, and drag it to the right to increase the distance between the rectangles. (You can hold the *Shift* key while dragging to ensure that the movement is directly to the right.)

4. Create the mediating variable.
   a. Select the Add Observed Variable tool, and then click in the diagram above the path from *support* to *perform*.
   b. In the Contextual Toolbar, select *satis* with the *Variable* control.
5. Create the paths to and from the mediating variable.
   a. Select the Add Path tool.
   b. Click in the upper right of the support rectangle (it will highlight when you hover over it), and drag a path to the lower left of the satis rectangle (it will highlight when you can release to connect the path).
   c. Continuing with the tool, draw a path from the lower right of the satis rectangle to the upper left of the perform rectangle.

6. Clean up the direction of the error term.
   We want the error for each of the endogenous variables to be to the right of the rectangle. The error for satis may have been created in another direction. If so,
   a. choose the Select tool;
   b. click in the satis rectangle;
   c. click on one of the Error Rotation buttons, in the Contextual Toolbar until the error is to the right of the rectangle.

7. Clean up the location of the paths.
   If you do not like where the paths have been connected to the rectangles, use the Select tool, to click on the path, and then simply click on where it connects to a rectangle and drag the endpoint.

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

9. To fit the model in Two-level model with gsem, continue with the previous diagram, and put the builder in gsem mode by clicking on the button.

10. Create the multilevel latent variable corresponding to the random intercept for satis.
    a. Select the Add Multilevel Latent Variable tool, and click above the rectangle for satis.
    b. In the Contextual Toolbar, click on the button.
    c. Select the nesting level and nesting variable by selecting 2 from the Nesting depth control and selecting branch > Observations in the next control.
    d. Specify M1 as the Base name.
    e. Click on OK.

11. Create the multilevel latent variable corresponding to the random intercept for perform.
    a. Select the Add Multilevel Latent Variable tool, and click above the rectangle for satis and to the right of the branch1 double oval.
    b. In the Contextual Toolbar, click on the button.
    c. Select the nesting level and nesting variable by selecting 2 from the Nesting depth control and selecting branch > Observations in the next control.
    d. Specify M2 as the Base name.
    e. Click on OK.
12. Draw paths from the multilevel latent variables to their corresponding endogenous variables.
   a. Select the Add Path tool, 
   b. Click in the bottom of the \textit{branch}_1 double oval, and drag a path to the top of the \textit{satis} rectangle.
   c. Continuing with the tool, click in the bottom of the \textit{branch}_2 double oval, and drag a path to the top of the \textit{perform} rectangle.

13. Estimate again.

   Click on the \textbf{Estimate} button, , in the Standard Toolbar, and then click on \textbf{OK} in the resulting \textit{GSEM estimation options} dialog box.

   You can open a completed diagram for the first model in the Builder by typing
   \texttt{. webgetsem sem_med}

   You can open a completed diagram for the second model in the Builder by typing
   \texttt{. webgetsem gsem_mlmed}

References


Also see

[SEM] \textbf{example 38g} — Random-intercept and random-slope models (multilevel)

[SEM] \textbf{gsem} — Generalized structural equation model estimation command

[SEM] \textbf{intro 5} — Tour of models