Below we discuss random-intercept and random-slope models in the context of multilevel models, and specifically, 2-level models, although we could just as well use higher-level models (see [SEM] Example 39g). Some people refer to these models as random-effects models and as mixed-effects models.

To demonstrate random-intercept and random-slope models, we will use the following data:

```
. use https://www.stata-press.com/data/r16/gsem_nlsy
(NLSY 1968)
. describe
Contains data from https://www.stata-press.com/data/r16/gsem_nlsy.dta
obs: 2,763  NLSY 1968
vars:  21  29 Mar 2018 11:30
(_dta has notes)

     variable name type format label variable label
--------- ------------- ------- -------- ------------------------
    idcode    int %8.0g  NLS ID
       year    int %8.0g  interview year
     birth_yr   byte %8.0g  birth year
       age    byte %8.0g  age in current year
        race   byte %8.0g  race
        msp    byte %8.0g   1 if married, spouse present
     nev_mar   byte %8.0g  1 if never married
      grade    byte %8.0g  current grade completed
     collgrad   byte %8.0g  1 if college graduate
     not_smsa   byte %8.0g  1 if not SMSA
       c_city    byte %8.0g  1 if central city
        south   byte %8.0g  1 if south
      ind_code   byte %8.0g  industry of employment
       occ_code   byte %8.0g  occupation
         union    byte %8.0g  1 if union
       wks_ue    byte %8.0g  weeks unemployed last year
      ttl_exp    float %9.0g  total work experience
        tenure    float %9.0g  job tenure, in years
         hours    int %8.0g  usual hours worked
     wks_work    int %8.0g  weeks worked last year
      ln_wage    float %9.0g  ln(wage/GNP deflator)
```

Sorted by: idcode  year

. notes
_dta:
2. These data were subsetted for purposes of demonstration.
These 2-level data are recorded in long form, that is, each observation corresponds to a year within a subject and the full set of data is spread across repeated observations.

```
.list id year ln_wage union grade in 1/20, sepby(idcode)
```

<table>
<thead>
<tr>
<th>idcode</th>
<th>year</th>
<th>ln_wage</th>
<th>union</th>
<th>grade</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1970</td>
<td>1.451214</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>2</td>
<td>1971</td>
<td>1.02862</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>3</td>
<td>1972</td>
<td>1.589977</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>4</td>
<td>1973</td>
<td>1.780273</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>5</td>
<td>1975</td>
<td>1.777012</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>6</td>
<td>1977</td>
<td>1.778681</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>7</td>
<td>1978</td>
<td>2.493976</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>8</td>
<td>1980</td>
<td>2.551715</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>9</td>
<td>1983</td>
<td>2.420261</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>10</td>
<td>1985</td>
<td>2.614172</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>11</td>
<td>1987</td>
<td>2.536374</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>12</td>
<td>1988</td>
<td>2.462927</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>13</td>
<td>1971</td>
<td>1.360348</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>14</td>
<td>1972</td>
<td>1.206198</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>15</td>
<td>1973</td>
<td>1.549883</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>16</td>
<td>1975</td>
<td>1.832581</td>
<td>.</td>
<td>12</td>
</tr>
<tr>
<td>17</td>
<td>1977</td>
<td>1.726721</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>18</td>
<td>1978</td>
<td>1.68991</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>19</td>
<td>1980</td>
<td>1.726964</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>20</td>
<td>1982</td>
<td>1.808289</td>
<td>1</td>
<td>12</td>
</tr>
</tbody>
</table>

In the repeated observations for a subject, some variables vary (they are at the observation level, such as \( \text{ln\_wage} \)) and other variables do not vary (they are at the subject level, such as \( \text{grade} \)).

When using \texttt{gsem}, multilevel data must be recorded in the long form except in one case. The exception is latent growth curve models, which can be fit in the long or wide form. In the wide form, there is one physical observation for each subject and multiple variables within subject, such as \textit{ln\_wage}	extsubscript{1970}, \textit{ln\_wage}	extsubscript{1971}, and so on. Researchers from a structural equation modeling background think about latent growth models in the wide form; see \texttt{SEM Example 18}.

In all other cases, if your data are in the wide form, use Stata’s \texttt{reshape} command (see \texttt{[D reshape}) to convert the data to long form.

See \textit{Structural models 1: Linear regression} and \textit{Multilevel mixed-effects models} in \texttt{SEM Intro 5} for background.

**Remarks and examples**

Remarks are presented under the following headings:

- Random-intercept model, single-equation formulation
- Random-intercept model, within-and-between formulation
- Random-slope model, single-equation formulation
- Random-slope model, within-and-between formulation
- Fitting the random-intercept model with the Builder
- Fitting the random-slope model with the Builder
Random-intercept model, single-equation formulation

There are two formulations of the random-intercept model, which we call the single-equation formulation and the within-and-between formulation. Results from both formulations are identical unless you have observations with missing values, in which case the within-and-between formulation will sometimes use more of the data.

We will show you both formulations, but the single-equation formulation makes a good starting point. The model we wish to fit is

\[
\begin{align*}
\ln(wage) &= \varepsilon_1 + grade + 1\cdot union + idcode_1 \\
\end{align*}
\]

Figure 1

We use factor-variable notation in the diagram above; see [SEM] Example 37g.

We are using multilevel data. \(\ln(wage)\) and \(union\) (union membership) vary at the observation level, while \(grade\) (school completion) varies at the subject level. We have used shading to emphasize that.

In this model, we are including a random intercept (a random effect) at the subject level. Double-ringed \(idcode\) is saying, “I am a latent variable at the \(idcode\) level—meaning I am constant within identification codes and vary across identification codes—and I correspond to a latent variable named \(M1\).” The \(M1\) part of the statement came from the subscript 1; the \(M\) part is fixed.

Double-ringed \(idcode\) indicates a latent variable constant within \(idcode\)—a random effect. And the fact that the path from the latent variable is pointing to a box and not to another path means that the latent variable is used as a random intercept rather than a random slope. By the way, variable \(idcode\) in the data contains each subject’s identification number.

Using command syntax, we can fit this model by typing

```
. gsem (ln_wage <- i.union grade M1[idcode])
Fitting fixed-effects model:
Iteration 0:  log likelihood =  -925.06629
Iteration 1:  log likelihood =  -925.06629
Refining starting values:
Grid node 0:  log likelihood =  -763.3769
Fitting full model:
Iteration 0:  log likelihood =  -763.3769
Iteration 1:  log likelihood =  -622.04625 (backed up)
Iteration 2:  log likelihood =  -613.54948
Iteration 3:  log likelihood =  -607.56242
Iteration 4:  log likelihood =  -607.49246
Iteration 5:  log likelihood =  -607.49233
Iteration 6:  log likelihood =  -607.49233
```

Generalized structural equation model
Number of obs = 1,904
Response : ln_wage
Family : Gaussian
Link : identity
Log likelihood = -607.49233

( 1) [ln_wage]M1[idcode] = 1

| Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|-------|-----------|------|-----|----------------------|
| ln_wage |          |      |     |                      |
| 1.union | .1637408  | .0227254 | 7.21 | 0.000 | .1191998 - .2082818 |
| grade   | .0767919  | .0067923 | 11.31| 0.000 | .0634791 - .0901046 |
| M1[idcode] | 1 (constrained) | | | |
| _cons   | .7774129  | .0906282 | 8.58 | 0.000 | .5997848 - .955041  |

var(M1[idcode]) = .080247 - .0073188 | .0671113 - .0959537 |
var(e.ln_w~e) = .078449 - .0028627 | .0730342 - .0842653 |

Notes:

1. The ln_wage <- M1[idcode] coefficient is constrained to be 1. Such constraints are automatically supplied by gsem to identify the latent variable. Our model is

   \[ \ln \text{wage} = \cdots + \beta_3 \times M1[\text{idcode}] + \_\text{cons} \]

   \[ = \cdots + 1 \times M1[\text{idcode}] + 0.7774 \]

   Thus M1[idcode] is being used as a random intercept.

   Remember that the square bracketed [idcode] means that M1 is constant within idcode and varies only across idcode.

2. The variance of our random intercept is estimated to be 0.0802, which is greater than the estimated error variance of 0.0784.

3. Although it is obvious in this case that the latent variable (random intercept) has sufficient variance that it cannot be ignored, we can test whether the variance is large enough that we could not ignore it. The test will be up against a boundary (variances cannot be less than 0), and so the test will be conservative. To perform the test, we would type

   . gsem (ln_wage <- i.union grade) // fit model w/o random intercept
   . estimates store without
   . gsem (ln_wage <- i.union grade M1[idcode]) // fit model w/ random intercept
   . estimates store with
   . lrtest without with // order of arguments unimportant
Random-intercept model, within-and-between formulation

The other way to write the random-intercept model is

\[
\text{ln}_wage \epsilon_1 \text{grade} 1.\text{union} \text{idcode}_1 \epsilon_2
\]

\[
\text{ln}_wage \epsilon_1
\text{grade} 1.\text{union} \text{idcode}_1 \epsilon_2
\]

Figure 2

Do not read grade pointing to double-ringed idcode as grade being a predictor of idcode. That would make no sense. Double rings indicate a latent variable, and grade is a predictor of a latent variable. In particular, the subscript 1 on idcode indicates that the latent variable is named M1. Thus grade is a predictor of M1. The idcode inside the double rings says that M1 is constant within idcode. Thus grade, which itself does not vary within idcode, is a predictor of M1, which does not vary within idcode; said more elegantly, grade is a predictor of M1 at the subject level.

It is logically required that grade vary at the same or higher level as M1[idcode], and gsem will check that requirement for you.

In this model, M1[idcode] contains both the random intercept and the grade effect. There is now an equation for M1[idcode], with an error associated with it, and it will be the variance of the error term that will reflect the variance of the random intercept.
To fit this within-and-between formulation of our model, we type

```
  . gsem (ln_wage <- i.union M1[idcode]) (M1[idcode] <- grade)
```

Fitting fixed-effects model:
Iteration 0:  log likelihood =  -1091.655
Iteration 1:  log likelihood =  -1091.655

Refining starting values:
Grid node 0:  log likelihood =  -886.5024

Fitting full model:
Iteration 0:  log likelihood =  -886.5024  (not concave)
Iteration 1:  log likelihood =  -683.7337
Iteration 2:  log likelihood =  -630.9133
Iteration 3:  log likelihood =  -608.1454
Iteration 4:  log likelihood =  -607.4938
Iteration 5:  log likelihood =  -607.4923
Iteration 6:  log likelihood =  -607.4923

Generalized structural equation model  Number of obs  = 1,904
Response :  ln_wage  
Family :  Gaussian  
Link :  identity  
Log likelihood =  -607.4923

( 1)  [ln_wage]M1[idcode] = 1

|                | Coef.  | Std. Err. | z     | P>|z|  | [95% Conf. Interval] |
|----------------|--------|-----------|-------|------|----------------------|
| ln_wage        |        |           |       |      |                      |
| 1.union        | .16374| .0227254  | 7.21  | 0.000| .1191998 .2082818   |
| M1[idcode]     | 1      | (constrained) |       |      |                      |
| _cons          | .77741| .0906282  | 8.58  | 0.000| .5997848 .955041    |
| M1[idcode]     |        |           |       |      |                      |
| grade          | .07679| .0067923  | 11.31 | 0.000| .0634791 .0901046   |
| var(e.M1[idcode]) | .08024| .0073188  |       |      | .0671113 .0959537  |
| var(e.ln_w-e)  | .07844| .0028627  |       |      | .0730342 .0842653  |

Notes:

1. Results are identical to what we previously obtained.
2. The within-and-between formulation is equivalent to the single-equation formulation if there are no missing values in the data.
3. In this simple model, the two formulations are also equivalent even in the presence of missing values.
4. If M1[idcode] were also being used to predict another endogenous variable, then missing values in grade would only cause the equation for the other endogenous variable to have to omit those observations in the within-and-between formulation.
Random-slope model, single-equation formulation

Let us now turn to random slopes. Because it is generally—not always—a good idea to include random intercepts with random slopes, we are going to include both. In addition, we are going to complicate our model by adding an interaction term between union membership and grade so we can make another point that we will not explain until the next section.

The model we wish to fit is

\[
\text{ln\_wage} = \varepsilon + \beta_1 \text{grade} + 1.\text{union} + \beta_4 \times \text{M2[idcode]} 
\]

Ignore the interaction between union membership and grade. We could have omitted it from this example, but we want to show later the strikingly different way that interaction can be written in the within-and-between formulation.

In this model, we have double-ringed idcode, just as we did in a previous section introducing a random intercept into the model. This time, however, we also have a second double-ringed idcode adding a random slope. When a path from a latent variable points to another path, it is specifying a random slope. When specifying a random slope for a variable, you still include the variable in the usual, fixed-slope way, and then you add the extra component.

The result of the extra component will be to add an interaction into the model. 1.union will affect ln\_wage, just as we have drawn, and the extra component will add 1.union \times M2[idcode]. That is, the effect of 1.union in our model will be

\[
\text{ln\_wage} = \cdots + \beta_3 \times 1.\text{union} + \beta_4 \times 1.\text{union} \times \text{M2[idcode]} + \cdots \\
= \cdots + \beta_3 \times 1.\text{union} + \beta_4 \times \text{M2[idcode]} \times 1.\text{union} + \cdots \\
= \cdots + (\beta_3 + \beta_4 \times \text{M2[idcode]}) \times 1.\text{union} + \cdots 
\]

The fixed-plus-random, total slope is \( \beta_3 + \beta_4 \times \text{M2[idcode]} \). Latent variable M2 has an arbitrary scale, and therefore coefficient \( \beta_4 \) cannot be identified. So constraining \( \beta_4 = 1 \) results in the total slope being \( \beta_3 + \text{M2[idcode]} \), which is exactly how you would expect a fixed-plus-random slope to look. In other words, drawing the path from idcode_2 to the path with coefficient \( \beta_3 \) indicates that M2[idcode] is added to \( \beta_3 \).
To fit this model in the command language, we type:

```
.gsem (ln_wage <- i.union grade i.union#c.grade M1[idcode] 1.union#M2[idcode])
```

Fitting fixed-effects model:
Iteration 0: log likelihood = -925.06629
Iteration 1: log likelihood = -925.06629

Refining starting values:
Grid node 0: log likelihood = -869.92256

Fitting full model:
Iteration 0: log likelihood = -869.92256 (not concave)
Iteration 1: log likelihood = -727.15806 (not concave)
Iteration 2: log likelihood = -711.74718 (not concave)
Iteration 3: log likelihood = -684.33867 (not concave)
Iteration 4: log likelihood = -665.94123 (not concave)
Iteration 5: log likelihood = -610.14526
Iteration 6: log likelihood = -589.89989
Iteration 7: log likelihood = -582.24119
Iteration 8: log likelihood = -581.298
Iteration 9: log likelihood = -581.29004
Iteration 10: log likelihood = -581.29003

Generalized structural equation model

```
Response : ln_wage
Family : Gaussian
Link : identity
Log likelihood = -581.29003
```

( 1) [ln_wage]M1[idcode] = 1
( 2) [ln_wage]1.union#M2[idcode] = 1

| Coef.  | Std. Err. | z    | P>|z|  | [95% Conf. Interval] |
|--------|-----------|-----|------|----------------------|
| ln_wage
1.union
grade  | 0.1199049 | .1508189 | 0.80  | 0.427  | -.1756946  | .4155045 |
| .0757883 | .0081803 | 9.26 | 0.000 | .0597552 | .0918215 |
| union#
c.grade 1 | 0.0019983 | .0113534 | 0.18  | 0.860  | -.020254  | .0242506 |
| M1[idcode] 1 (constrained) |
| union#
M2[idcode] 1 (constrained) |
| _cons  | .7873884 | .1086476 | 7.25  | 0.000  | .574443   | 1.000334 |
| var(M1[idcode])  | .0927931 | .0088245 | 0.770136 | .1118056 |
| var(M2[idcode])  | .0823065 | .018622  | .052826 | .1282392 |
| cov(M1[idcode], M2[idcode]) | -.0549821 | .0116103 | -4.74 | 0.000  | -.077738  | -.0322263 |
| var(e.ln_w-e)  | .0720873 | .0027135 | .0669603 | .0776068 |
Notes:

1. $M1[idcode]$ is the random intercept. The coefficient on it is constrained to be 1, just as previously and just as we would expect.

2. The coefficient on $1.\text{union}$ is the fixed part of the slope of $\text{union}$.

3. $M2[idcode]$ is the random part of the slope of $\text{union}$.

   The coefficient on $1.\text{union}#M2[idcode]$ is constrained to be 1, just as we would expect. $1.\text{union}#M2[idcode]$ is the way Stata writes $1.\text{union} \times M2[idcode]$.

4. There is an unexpected term in the output, $0.\text{union}#M2[idcode]$, shown with coefficient 0. The first thing to remember about unexpected terms is that they are irrelevant if their coefficients are 0. $gsem$ reports the coefficient as being 0 (omitted), which is $gsem$'s way of saying, “Here is a line that I did not even include in the model.” There are a lot of terms $gsem$ could tell us about that were not included in the model, so why did $gsem$ feel obligated to tell us about this term? The term has to do with how Stata tracks base levels of factor variables.

   There is a setting—`set showbaselevels off`—that will prevent lines like that from being displayed. There is also a setting—`set showbaselevels all`—that will show even more of them! The default is `set showbaselevels on`.

5. We specified the interaction as $1.\text{union}#M2[idcode]$ rather than $i.\text{union}#M2[idcode]$. Even so, using `#.\text{union}#M2[idcode]` or `i.\text{union}#M2[idcode]` makes no difference because union takes on two values. If union took on three values, however, think about how we would diagram the model. We would have two latent variables, and we would want $1.\text{union}#M2[idcode]$ and $2.\text{union}#M3[idcode]$. If union took on three or more values, typing `i.\text{union}#M2[idcode]` simply would not produce the desired result.

Random-slope model, within-and-between formulation

To properly demonstrate the within-and-between formulation, we need a more complicated model; we made one in the previous section when we included $1.\text{union}#c.\text{grade}$ and then told you to ignore it.

Pretend that we had omitted $1.\text{union}#c.\text{grade}$ from the random-slope, single-equation formulation model. It would have looked like this:
Let's call this model Simple formulation 1 as compared with the model that we fit in the previous section, which we will call Demonstrated formulation 1. We could have fit Simple formulation 1 by typing

```
.gsem (ln_wage <- i.union grade M1[idcode] 1.union#M2[idcode])
```

The corresponding within-and-between model, which we will call Simple formulation 2, would look something like this:

![Figure 5. Simple formulation 2](image)

We say that it would look something like the above because Simple formulations 1 and 2 are not identical models. In particular, there is nothing in Simple formulation 2 that corresponds to the correlation between \( M1[idcode] \) and \( M2[idcode] \) in Simple formulation 1. Other than that, the models are identical. In Simple formulation 1, grade directly affects \( \ln \text{wage} \). In Simple formulation 2, grade affects \( M1[idcode] \) and \( M1[idcode] \) affects \( \ln \text{wage} \). The results are the same either way. Many researchers prefer Simple formulation 2 because it visually separates the within (subject) and between (subject) levels.

But as we said, the two formulations are not identical. They would be identical if we added a curved covariance path between \( \epsilon_2 \) and \( idcode_2 \), but Stata will not allow us to do that.

On the other hand, if you wanted to fit the simple model without the correlation, you could do it in either formulation. For Simple formulation 1, you would type

```
.gsem (ln_wage <- i.union grade M1[idcode] 1.union#M2[idcode]), ///
cov(M1[idcode]*M2[idcode]@0)
```

For Simple formulation 2, you would type

```
.gsem (ln_wage <- i.union M1[idcode] 1.union#M2[idcode]) (M1[idcode] <- grade)
```

Either way, results would be identical.
In more complicated models, you can correlate the random intercepts and slopes even in a second formulation. Consider Demonstrated formulation 2:

\[
\text{ln}_\text{wage} = \varepsilon_1 + \text{grade} + 1.\text{union} + \varepsilon_2 \text{idcode} + \varepsilon_3 \text{idcode}^2
\]

Figure 6. Demonstrated formulation 2

In this model, we allow correlation between \(\varepsilon_3\) and \(\varepsilon_2\)—which Stata does allow—and that is the same as allowing correlation between \(M_1[\text{idcode}]\) and \(M_2[\text{idcode}]\) in the formulation-1 model. The general rule is that formulation 2 can be used to correlate the random intercepts and random slopes when both \(M_1\) and \(M_2\) are (latent) exogenous or (latent) endogenous.

Demonstrated formulation 2 corresponds to Demonstrated formulation 1. In Demonstrated formulation 1, we included \(\text{ln}_\text{wage} \leftarrow i.\text{union} \# c.\text{grade}\). Do you see how that term is implied by the path diagram above? Variable grade affects \(M_2[\text{idcode}]\), which in turn affects the slope of 1.union. Affecting the slope is the same as an interaction.

And now you know why we complicated Demonstrated formulation 1. We did that so that we can show you Demonstrated formulation 2:

```
. gsem (ln_wage <- i.union M1[idcode] 1.union#M2[idcode])
> (M1[idcode] M2[idcode] <- grade), cov(e.M1[idcode]*e.M2[idcode])
```

Fitting fixed-effects model:
Iteration 0:  log likelihood =  -1091.655
Iteration 1:  log likelihood =  -1091.655

Refining starting values:
Grid node 0:  log likelihood =  -982.1826

Fitting full model:
Iteration 0:  log likelihood =  -982.1826 (not concave)
Iteration 1:  log likelihood =  -982.1826 (not concave)
Iteration 2:  log likelihood =  -677.1382 (not concave)
Iteration 3:  log likelihood =  -661.2666
Iteration 4:  log likelihood =  -615.6605
Iteration 5:  log likelihood =  -585.6940
Iteration 6:  log likelihood =  -581.3416
Iteration 7:  log likelihood =  -581.2901
Iteration 8:  log likelihood =  -581.2900
Generalized structural equation model

Number of obs = 1,904

Response : ln_wage
Family : Gaussian
Link : identity
Log likelihood = -581.29003

( 1) [ln_wage]M1[idcode] = 1
( 2) [ln_wage]1.union#M2[idcode] = 1

| Coef. | Std. Err. | z  | P>|z| | [95% Conf. Interval] |
|-------|-----------|----|-----|---------------------|
| ln_wage | 0.119905  | 0.1508188 | 0.80 | 0.427 | -.1756945 .4155045 |
| 1.union |          |          |      |        |                   |
| M1[idcode] | 1 (constrained) | | | |
| union#M2[idcode] | 1 | (constrained) | | | |
| _cons | 0.7873884 | 0.1086476 | 7.25 | 0.000 | 0.5744431 1.000334 |
| M1[idcode] | grade | .0757883 | 0.0081803 | 9.26 | 0.000 | 0.0597552 0.0918215 |
| M2[idcode] | grade | .0019983 | 0.0113534 | 0.18 | 0.860 | -.020254 0.0242506 |
| var(e.M1[idcode]) | 0.092793 | 0.0088245 | 0.0770136 | 0.1118055 |
| var(e.M2[idcode]) | 0.0823065 | 0.018622 | 0.052826 | 0.1282392 |
| cov(e.M1[idcode],e.M2[idcode]) | -.0549822 | 0.0116103 | -4.74 | 0.000 | -.077738 -.0322263 |
| var(e.ln_w-e) | 0.0720873 | 0.0027135 | .0669603 | .0776068 |

Note:
1. Results of the above are identical to the results of Demonstrated formulation 1.

Fitting the random-intercept model with the Builder

Use the diagram in Random-intercept model, single-equation formulation above for reference.

1. Open the dataset.
   In the Command window, type
   ```
   . use https://www.stata-press.com/data/r16/gsem_nlsy
   ```

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

3. Put the Builder in gsem mode by clicking on the button.
4. Create the endogenous variable.
   a. Select the Add observed variable tool, □, and then click in the diagram about one-third of the way in from the right and one-third of the way up from the bottom. After adding it, you can click inside the rectangle and move the variable if you wish.
   b. In the Contextual Toolbar, select \texttt{ln\_wage} with the Variable control.

5. Create the observed exogenous variables.

Select the Add observed variables set tool, ○○○, and then click in the diagram about one-third of the way in from the left and 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 and select grade;
   c. type \texttt{1.union} in the Variables control after grade (typing \texttt{1.union} rather than using the button to create \texttt{i.union} prevents the rectangle corresponding to the base category for this binary variable from being created);
   d. select Vertical in the Orientation control;
   e. click on OK.

If you wish, move the set of variables by clicking on any variable and dragging it.

6. Create the multilevel latent variable corresponding to the random intercept.
   a. Select the Add multilevel latent variable tool, ⊙, and click above the rectangle for grade.
   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 id\texttt{code} \textgreater Observations in the next control.
   d. Specify M1 as the Base name.
   e. Click on OK.

7. Create the paths from the exogenous variables to \texttt{ln\_wage}.
   a. Select the Add path tool, −.
   b. Click in the right side of the \texttt{1.union} rectangle (it will highlight when you hover over it), and drag a path to the left side of the \texttt{ln\_wage} rectangle (it will highlight when you can release to connect the path).
   c. Continuing with the − tool, draw paths from the right side of the grade rectangle to the left side of the \texttt{ln\_wage} rectangle and from the right side of the id\texttt{code}1 double oval to the left side of the \texttt{ln\_wage} rectangle.

8. Clean up the location of the paths.

If you do not like where the paths have been connected to the rectangles or oval, use the Select tool, , to click on the path, and then simply click on where it connects to a rectangle or oval and drag the endpoint.
   Click on the **Estimate** button, ![Estimate](https://www.stata-press.com/data/r16/gsem_nlsy), in the Standard Toolbar, and then click on **OK** in the resulting *GSEM estimation options* dialog box.

   You can open a completed diagram in the Builder by typing
   
   . webgetsem gsem_rint

---

**Fitting the random-slope model with the Builder**

Use the diagram in *Random-slope model, single-equation formulation* above for reference.

1. Open the dataset.

   In the Command window, type
   
   . use https://www.stata-press.com/data/r16/gsem_nlsy

2. Open a new Builder diagram.

   Select menu item **Statistics > SEM (structural equation modeling) > Model building and estimation**.

3. Put the Builder in *gsem* mode by clicking on the ![GSEM](https://www.stata-press.com/data/r16/gsem_nlsy) button.

4. Increase the width of the observed variable rectangles to accommodate the length of the name of the interaction term.

   From the SEM Builder menu, select **Settings > Variables > All observed...**

   In the resulting dialog box, change the first size to 1 and click on **OK**.

5. Create the endogenous variable.

   a. Select the Add observed variable tool, ![Add variable](https://www.stata-press.com/data/r16/gsem_nlsy), and then click in the diagram about one-third of the way in from the right and one-third of the way up from the bottom. After adding it, you can click inside the rectangle and move the variable if you wish.

   b. In the Contextual Toolbar, select `ln_wage` with the **Variable** control.

6. Create the observed exogenous variables.

   Select the Add observed variables Set tool, ![Add set](https://www.stata-press.com/data/r16/gsem_nlsy), and then click in the diagram about one-third of the way in from the left and one-third of the way up from the bottom.

   In the resulting dialog box, change the first size to 1 and click on **OK**.

   a. Select the **Select variables** radio button (it may already be selected);

   b. type `1.union` in the **Variables** control (typing `1.union` rather than using the ![Add variable](https://www.stata-press.com/data/r16/gsem_nlsy) button to create `i.union` prevents the rectangle corresponding to the base category for this binary variable from being created);

   c. use the **Variables** control and select `grade`;

   d. type `1.union#c.grade` in the **Variables** control after `grade`;

   e. select **Vertical** in the **Orientation** control;

   f. click on **OK**.

   If you wish, move the set of variables by clicking on any variable and dragging it.
6. Create the multilevel latent variable corresponding to the random intercept.
   a. Select the Add multilevel latent variable tool, \( \circ \), and click above the rectangle for \( \text{ln}_\text{wage} \).
   b. In the Contextual Toolbar, click on the \( \circ \) button.
   c. Select the nesting level and nesting variable by selecting \( 2 \) from the Nesting depth control and selecting \( \text{idcode} > \text{Observations} \) in the next control.
   d. Specify M1 as the Base name.
   e. Click on OK.

7. Create the paths from the exogenous variables to \( \text{ln}_\text{wage} \).
   a. Select the Add path tool, \( \rightarrow \).
   b. Click in the right side of the \( 1.\text{union} \) rectangle (it will highlight when you hover over it), and drag a path to the left side of the \( \text{ln}_\text{wage} \) rectangle (it will highlight when you can release to connect the path).
   c. Continuing with the \( \rightarrow \) tool, draw paths from the right sides of the \( \text{grade} \) and \( 1.\text{union}#\text{c.grade} \) rectangles to the left side of the \( \text{ln}_\text{wage} \) rectangle and from the bottom of the \( \text{idcode}_1 \) double oval to the top of the \( \text{ln}_\text{wage} \) rectangle.

8. Create the random slope.
   a. Select the Add multilevel latent variable tool, \( \circ \), and click above the path from \( 1.\text{union} \) to \( \text{ln}_\text{wage} \).
   b. In the Contextual Toolbar, click on the \( \circ \) button.
   c. Select the nesting level and nesting variable by selecting \( 2 \) from the Nesting depth control and selecting \( \text{idcode} > \text{Observations} \) in the next control.
   d. Specify M2 as the Base name.
   e. Click on OK.
   f. Select the Add path tool, \( \rightarrow \).
   g. Click in the bottom of the \( \text{idcode}_2 \) double oval, and drag a path to the path between \( 1.\text{union} \) and \( \text{ln}_\text{wage} \).

9. Create the covariance between the random slope and random intercept.
   a. Select the Add covariance tool, \( \wedge \).
   b. Click in the top-right quadrant of the \( \text{idcode}_2 \) double oval, and drag a covariance to the top left of the \( \text{idcode}_1 \) double oval.

10. Clean up paths and covariance.
    If you do not like where a path has been connected to its variables, use the Select tool, \( \blacktriangleleft \), to click on the path, and then simply click on where it connects to a rectangle and drag the endpoint. Similarly, you can change where the covariance connects to the latent variables by clicking on the covariance and dragging the endpoint. You can also change the bow of the covariance by clicking on the covariance and 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 **GSEM estimation options** dialog box.

   You can open a completed diagram in the Builder by typing

   . webgetsem gsem_rslope

**Reference**


**Also see**

-[SEM] Example 39g — Three-level model (multilevel, generalized response)
-[SEM] Example 42g — One- and two-level mediation models (multilevel)
-[SEM] Intro 5 — Tour of models
-[SEM] gsem — Generalized structural equation model estimation command