Specifying appropriate null models with longitudinal SEMs

Sven O. Spieß

German Stata User Group Meeting

6/22/2018

Introduction

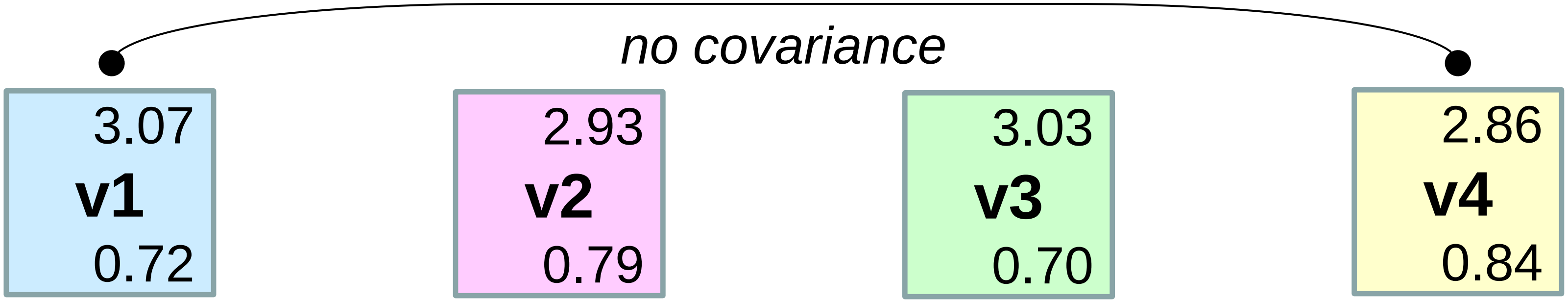
- No immediate indicator of the overall quality of the respective model
- Instead typically reliance on several indicators
- Among those so-called fit indices such as the comparative fit index, **CFI**, and the Tucker-Lewis index, **TLI**

- Fit indices are computed by comparing the model of interest with an *assumed* worst-fitting baseline model

- Some authors have made the case that the standard baseline model is only appropriate for single-group, single-occasion models (e.g. Little, Preacher, Card, & Selig, 2007; Widaman & Thompson, 2003)

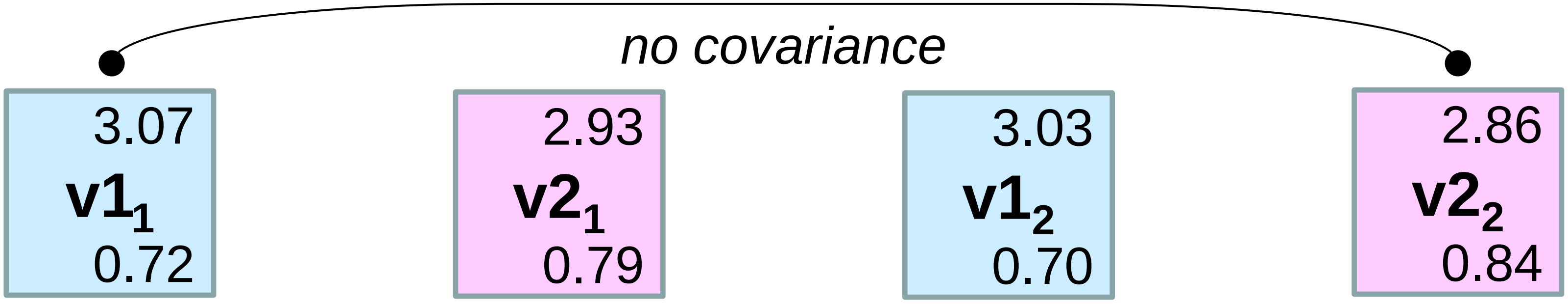
The Independence Model

- Default worst-fitting baseline the so-called **independence model**:
  - All observed variables are restricted to have zero covariance; i.e. are completely independent
  - Model without latent constructs
  - Means and variances estimated freely



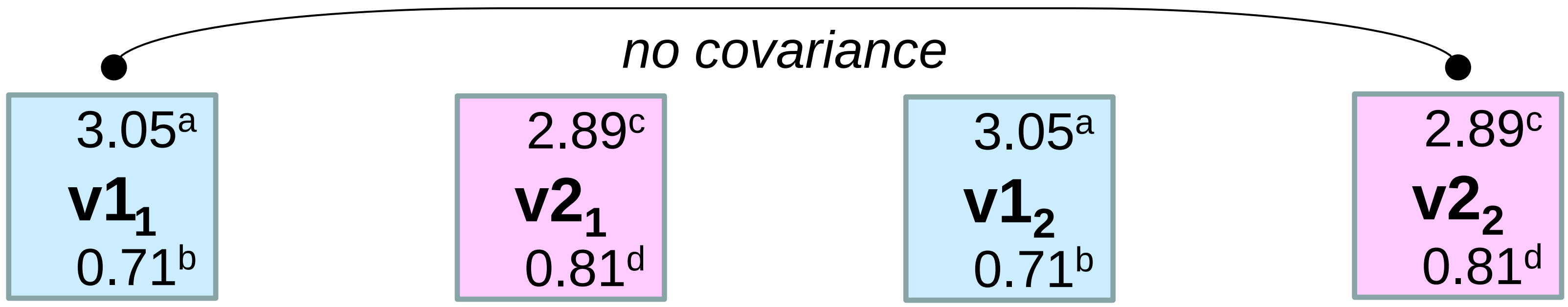
A Longitudinal Baseline Model

- What could possibly be worse?



A Longitudinal Baseline Model

- What could possibly be worse?
- How about on top of no covariance, adding the additional restriction that the means and variances are the same over time:

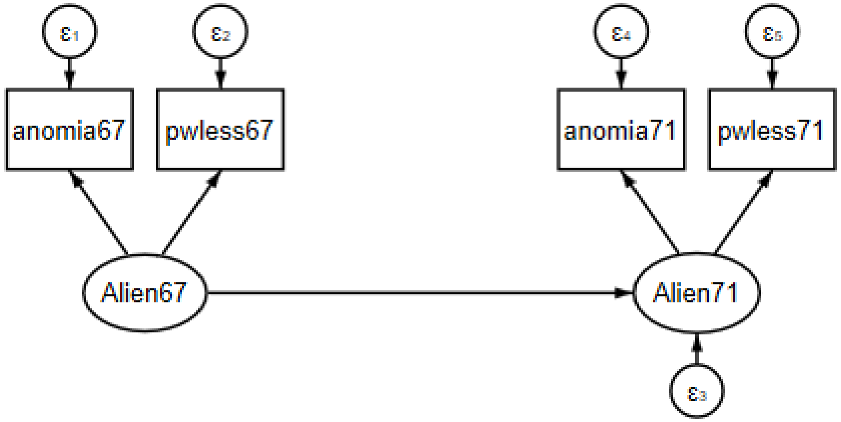


An Example

- For easy reproduction the following example is based on [SEM] manual data set *sem_sm2.dta*:

```
. use http://www.stata-press.com/data/r15/sem_sm2.dta
(Structural model with measurement component)
```

- Simplified target model:



An Example *(continued)*

- Estimate model:

```
sem ///
(anomia67 pwless67 <- Alien67) /// measurement piece
(anomia71 pwless71 <- Alien71) /// measurement piece
(Alien71 <- Alien67) // structural piece
```

(output omitted)

An Example

- How well are we doing with the default baseline?

```
estat gof, stat(all)

----------------------------------------------------------------------------
Fit statistic        |      Value   Description
---------------------+------------------------------------------------------
Likelihood ratio     |
          chi2_ms(1) |     61.220   model vs. saturated
            p > chi2 |      0.000
          chi2_bs(6) |   1565.905   baseline vs. saturated
            p > chi2 |      0.000
---------------------+------------------------------------------------------

           (output omitted)

---------------------+------------------------------------------------------
Baseline comparison  |
                 CFI |      0.961   Comparative fit index
                 TLI |      0.768   Tucker-Lewis index
---------------------+------------------------------------------------------
```

An Example *(continued)*

- With the `-covstruct()-` option we can easily reproduce the default baseline model:

```
sem ///
(anomia67 anomia71 pwless67 pwless71) /// measurement piece
, covstruct(_Ex, diagonal)

(output omitted)
```

An Example *(continued)*

- Accessing the stored results we can compute the fit indices of our target model with the reproduced (default) baseline.

- The indices are defined as follows:

```
                        (chi2_ms - df_ms)
CFI = 1 - ------------------------------------------
          max((chi2_ms - df_ms), (chi2_base - df_base))


      (chi2_base/df_base) - (chi2_ms/df_ms)
TLI = ------------------------------------
           (chi2_base/df_base) – 1
```

- (Cf. `-view mansection SEM methodsandformulasforsem-`)

An Example *(continued)*

- Plugging in the values we get the following results:

```
CFI = 1 - [max((61.220 - 1), 0) /
           max((61.220 - 1), (1565.905 - 6), 0)]
    = .96139481

TLI = ((1565.905/6) - (61.220/1)) / ((1565.905/6) - 1)
    = .76836885

(Note: estat gof results: CFI = .96139481; TLI = .76836885)
```

```
. assert 1 - [max($diff_m, 0) / max($diff_m, $diff_db, 0) ] ==
$cfi_db

. assert (($chi2_db/$df_db) - ($chi2_m/$df_m)) / (($chi2_db/$df_db) -
1) == $tli_db
```

An Example *(continued)*

- Things are looking good, so now we can go ahead with the *longitudinal* baseline model:

```
sem ///
(anomia67 anomia71 pwless67 pwless71) /// measurement piece
,    covstruct(_Ex, diagonal)         ///
     mean(           /// constrain corresponding means to equality
             anomia67@m1 anomia71@m1  ///
             pwless67@m2 pwless71@m2  ///
             )                        ///
    var(     /// constrain corresponding variances to equality
             anomia67@v1 anomia71@v1  ///
             pwless67@v2 pwless71@v2  ///
             )
```

An Example *(continued)*

```
[…]

 ( 1)  [/]var(anomia67) - [/]var(anomia71) = 0
 ( 2)  [/]var(pwless67) - [/]var(pwless71) = 0
 ( 3)  [/]mean(anomia67) - [/]mean(anomia71) = 0
 ( 4)  [/]mean(pwless67) - [/]mean(pwless71) = 0
------------------------------------------------------------------------------
              |                 OIM
              |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
mean(anomia67)|      13.87   .0810246   171.18   0.000     13.71119    14.02881
mean(anomia71)|      13.87   .0810246   171.18   0.000     13.71119    14.02881
mean(pwless67)|     14.785   .0720539   205.19   0.000     14.64378    14.92622
mean(pwless71)|     14.785   .0720539   205.19   0.000     14.64378    14.92622
--------------+---------------------------------------------------------------
 var(anomia67)|   12.23713   .4008405                      11.47618    13.04853
 var(anomia71)|   12.23713   .4008405                      11.47618    13.04853
 var(pwless67)|   9.677445   .3169952                      9.075669    10.31912
 var(pwless71)|   9.677445   .3169952                      9.075669    10.31912
------------------------------------------------------------------------------
LR test of model vs. saturated: chi2(10)  =   1580.51, Prob > chi2 = 0.0000
```

An Example *(continued)*

- Behold:

```
CFI = 1 - [max((61.220 - 1), 0) /
           max((61.220 - 1), (1580.508 - 10), 0)]
    = .96165545

TLI = ((1580.508/10) - (61.220/1)) / ((1580.508/10) - 1)
    = .61655454



(Note: estat gof results: CFI = .96139481; TLI = .76836885)
```

Conclusions

- As expected, for the CFI the longitudinal baseline appears to be actually slightly worse-fitting (i.e. CFI improves minimally)

- **However**, increase in *df*'s by a factor of 1,67 due to the added constraints and their greater impact on the TLI results in a substantially <u>decreased fit</u> for the longitudinal baseline:
  - Default:
    ```
    TLI = ((1565.905/6) - (61.220/1)) / ((1565.905/6) - 1)
     = .76836885
    ```
  - Longitudinal:
    ```
    TLI = ((1580.508/10) - (61.220/1)) / ((1580.508/10) - 1)
     = .61655454
    ```

- That is, given the apparent high stability in means and variances over time! (χ^2 values *very* similar between the two baselines)

Conclusions *(continued)*

- As the purpose of this talk was primarily instructional, we should be careful not to over-interpret the results of a poor model...

- …however, due to differences in *df*'s and temporal (in-)stability the general unpredictability of the effect of longitudinal versus the default independence baseline model on fit indices remains

- So, should we bother with hassle of custom longitudinal baselines?
  - In general default baseline performs reasonably well
  - Additionally, differences become smaller the better a target model performs (i.e. the closer fit indices get to 1)
  - Nevertheless, if you (or your reviewer ☺) agree that for longitudinal (or MGCFA) models particular assumptions for a reasonable baseline apply you should do it "*the right way*"

References:

- Little, T. D. (2013). *Longitudinal structural equation modeling*. Guilford press.
- Little, T. D., Preacher, K. J., Selig, J. P., & Card, N. A. (2007). New developments in latent variable panel analyses of longitudinal data. *International journal of behavioral development*, *31*(4), 357-365.
- Widaman, K. F., & Thompson, J. S. (2003). On specifying the null model for incremental fit indices in structural equation modeling. *Psychological methods*, *8*(1), 16.