Tor Neilands posted on Thursday, September 08, 2016 - 10:36 pm

VanderWeele in "A Unification of Mediation and Interaction: A 4-Way Decomposition", Epidemiology, 25(5), 749-761, 2014, describes a counterfactuals-based approach to decompose the total effect of exposure X on outcome Y via mediator M through four effects: CDE, reference interaction (Int\_ref), mediated interaction (Int\_med), and pure indirect effect PIE. A colleague is seeking my help to obtain these four effects from analysis we've run in Mplus for a continuous exposure, continuous mediator, and continuous outcome with the model specification containing an interaction of X with M in line with Case 3, Figure 4.1 in Muthen, Muthen, and Asparouhov, 2016, p. 204. Can you tell me how to obtain the four quantities described above using Mplus? (Could it be as simple as Mplus already producing these same effects under different names?) Thanks so much, Tor Neilands

Bengt O. Muthen posted on Friday, September 09, 2016 - 4:16 pm

The 2015 VanderWeele book Explanation in Causal Inference discusses this in the context of a model with XM interaction on pages 377 and 378. Top of page 378 shows how to express the 4 effects in terms of model parameters and values of a continuous exposure (X) variable. This can be done in Model Constraint which also gives you SEs by the Delta method.

Tor Neilands posted on Tuesday, September 13, 2016 - 6:43 pm

Thanks, Bengt! Using the book chapter you referenced plus the article I cited (both cover pretty much the same ground it seems), I was able to reverse-engineer Dr. VanderWeele's PROC NLMIXED SAS code from his article and book appendices into Mplus Model Constraint syntax as you suggested to compute the 4 decomposition effects based on the model parameters.

I am grand mean centering all covariates C to compute effects at the means of the covariates. I am less clear on the advisability of grand mean centering X and M in performing an analysis of this type. For a standard linear regression with interaction, centering both X and M yields more interpretable main effects and it appears to make the counterfactual effects easier to interpret in this analysis, too. However, are there any reasons why one should one not center either X or M in this analysis?

Thanks again and thanks, too, for setting up and being so attentive to Mplus Discussion - this is a tremendous resource for the research community.

Tor Neilands

Bengt O. Muthen posted on Tuesday, September 13, 2016 - 6:52 pm

I am glad it worked out. If this is a common request perhaps we should add it automatically to the printing of our counterfactual effects. In the meantime, if you like, please send me your Mplus input so that we can create a FAQ on it.

I don't see a reason why one couldn't grand-mean center X and M.

Tor Neilands posted on Wednesday, September 14, 2016 - 8:54 am

I just sent along the Mplus input and output where the results match results generated in SAS using Dr. VanderWeele's sample SAS code.

I very much like the idea of printing out these counterfactual effects in a future release of Mplus. I believe they add value and should not be too hard to obtain since most are a linear combination or, in the case of proportion mediated, ratios of effects or linear combinations of effects Mplus is already showing.

I'm glad there is no reason not to center X and M. Centering X is working well in my application. I am re-thinking centering M, though, because when I grand mean center M in my analysis, the interaction reference effect IntRef becomes zero and its coefficient is added to that of the CDE to alter the value of the CDE. Any further comments on this issue would be much appreciated.

## Title:

VanderWeele (2014) 4-way interaction decomposition

Data:

File is index\_for\_tor\_080516\_for\_mplus.dat;

Variable:

- -

Names are	gender	gender	2 gender.	3 orient	tl orient2	orient3
bwlo1	bwlo2	bwlo3	bwlo4	subject	ninety	

sixes	pha9	flag18	stigma	timehiv	artevr	

missed age10 prop100 phq9bin phqstig phqbstig ;

Missing are .;

Usevariables are age10 TimeHIV ARTEVR Stigma PHQ9 phqstig prop100;

Analysis:

Type = General ;

Estimator = ML ;

## Model:

prop100 ON age10 (tc1)

TimeHIV (tc2)

ARTEVR (tc3)

Stigma (t1)

PHQ9 (t2)

phqstig (t3);

```
PHQ9 ON age10 (bc1)
```

TimeHIV (bc2)

ARTEVR (bc3)

Stigma (b1);

[PHQ9] (b0);

## Model Constraint:

New bcc cde intref intmed pie te

prop\_CDE prop\_IntRef prop\_IntMed Prop\_PIE Prop\_Med Prop\_Int Prop\_Elim

cc1 cc2 cc3 mstar a0 a1;

cc1=10; cc2=10; cc3=20;

mstar=0;

a0=0; a1=1;

$$bcc = bc1*cc1 + bc2*cc2 + bc3*cc3;$$

cde = (t1 + t3\*mstar)\*(a1-a0);

intref = t3\*(b0 + b1\*a0 + bcc - mstar)\*(a1-a0);

intmed = t3\*b1\*(a1-a0)\*(a1-a0);

pie = (t2\*b1 + t3\*b1\*a0)\*(a1-a0);

te = cde + intref + intmed + pie;

prop\_CDE = cde/te;

prop\_IntRef = intref/te;

prop\_IntMed = intmed/te;

prop\_PIE = pie/te;

prop\_med = (pie+intmed)/te;

prop\_int = (intref+intmed)/te;

prop\_elim = (intref+intmed+pie)/te;

Output:

CInterval;