How can I compare indirect effects in a multiple group model?

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July 1, 2024

A multiple group model is a statistical analysis technique used to examine the effects of one or more independent variables on a dependent variable in different groups or conditions. One aspect of this analysis is comparing the indirect effects of the independent variable on the dependent variable. This is done by estimating the indirect effects separately for each group and then comparing the estimates between the groups. The indirect effects can be compared using statistical tests or by examining the size and direction of the effects in each group. This comparison allows researchers to determine if the indirect effects differ significantly between the groups, providing valuable insights into the underlying mechanisms driving the relationship between the independent and dependent variables.

How can I compare indirect effects in a multiple group model? | Stata FAQ

Consider the following mediation model run as a multiple group structural equation model (sem) with science as the final response variable, math as the independent variable and read as the mediator variable for the four levels of grp.

use https://stats.idre.ucla.edu/stat/data/hsbanova, clear

sem (read <- math)(science <- read math), group(grp)

Endogenous variables

Observed: read science

Exogenous variables

Observed: math

Fitting target model:

Iteration 0: log likelihood = -2051.912

Iteration 1: log likelihood = -2051.912

Structural equation model Number of obs = 200

Grouping variable = grp Number of groups = 4

Estimation method = ml

Log likelihood = -2051.912

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| OIM

| Coef. Std. Err. z P>|z|

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Structural |

read <- |

math |

grp1 | .5118412 .1408644 3.63 0.000 .2357521 .7879304

grp2 | .4896411 .1699667 2.88 0.004 .1565124 .8227698

grp3 | .8001383 .1030434 7.77 0.000 .598177 1.0021

grp4 | .6923993 .1199016 5.77 0.000 .4573964 .9274022

_cons |

grp1 | 22.44033 6.632336 3.38 0.001 9.441189 35.43947

grp2 | 25.26262 8.593626 2.94 0.003 8.419422 42.10582

grp3 | 10.58565 5.792941 1.83 0.068 -.7683057 21.93961

grp4 | 17.2921 7.065407 2.45 0.014 3.444152 31.14004

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science <- |

read |

grp1 | .370112 .1421434 2.60 0.009 .0915161 .6487079

grp2 | .5359768 .1138689 4.71 0.000 .3127978 .7591559

grp3 | .5117303 .1229149 4.16 0.000 .2708215 .7526391

grp4 | .0790987 .132056 0.60 0.549 -.1797262 .3379236

math |

grp1 | .5519313 .1591829 3.47 0.001 .2399386 .8639239

grp2 | .4858494 .1412957 3.44 0.001 .2089149 .7627839

grp3 | .2365737 .1389155 1.70 0.089 -.0356956 .5088431

grp4 | .605095 .1401508 4.32 0.000 .3304044 .8797855

_cons |

grp1 | 4.500176 7.390037 0.61 0.543 -9.98403 18.98438

grp2 | 1.473353 7.166934 0.21 0.837 -12.57358 15.52029

grp3 | 10.8461 5.666826 1.91 0.056 -.2606705 21.95288

grp4 | 16.15488 6.662502 2.42 0.015 3.096616 29.21314

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Variance |

e.read |

grp1 | 61.51621 12.30324 41.56705 91.0395 grp2 | 70.4011 14.84186 46.57259 106.4213

grp3 | 47.59862 8.690279 33.28028 68.07722

grp4 | 46.68944 9.842998 30.88657 70.57773

e.science |

grp1 | 62.14594 12.42919 41.99257 91.97146

grp2 | 41.07736 8.659869 27.174 62.09428

grp3 | 43.14742 7.877605 30.16806 61.71096

grp4 | 36.6393 7.724243 24.23808 55.38552

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

Let's look at the direct and indirect effects using estat teffects.

estat teffects

Direct effects

| OIM

| Coef. Std. Err. z P>|z|

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Structural |

read <- |

math |

grp1 | .5118412 .1408644 3.63 0.000 .2357521 .7879304

grp2 | .4896411 .1699667 2.88 0.004 .1565124 .8227698

grp3 | .8001383 .1030434 7.77 0.000 .598177 1.0021

grp4 | .6923993 .1199016 5.77 0.000 .4573964 .9274022

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science <- |

read |

grp1 | .370112 .1421434 2.60 0.009 .0915161 .6487079

grp2 | .5359768 .1138689 4.71 0.000 .3127978 .7591559

grp3 | .5117303 .1229149 4.16 0.000 .2708215 .7526391

grp4 | .0790987 .132056 0.60 0.549 -.1797262 .3379236

math |

grp1 | .5519313 .1591829 3.47 0.001 .2399386 .8639239

grp2 | .4858494 .1412957 3.44 0.001 .2089149 .7627839

grp3 | .2365737 .1389155 1.70 0.089 -.0356956 .5088431

grp4 | .605095 .1401508 4.32 0.000 .3304044 .8797855

Indirect effects

| OIM

| Coef. Std. Err. z P>|z|

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Structural |
read <- |
math |
| 0 (no path)
----------+---
science <- |
read |
| 0 (no path)
math |
grp1 | .1894386 .0895064 2.12 0.034 .0140093 .3648678
grp2 | .2624363 .1068059 2.46 0.014 .0531006 .471772
grp3 | .409455 .1115931 3.67 0.000 .1907367 .6281734
grp4 | .0547679 .091926 0.60 0.551 -.1254038 .2349395

Note: identifies parameter estimates constrained to be equal across

groups.

Total effects

| OIM
| Coef. Std. Err. z P>|z|
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Structural |

read <- |

math |

grp1 | .5118412 .1408644 3.63 0.000 .2357521 .7879304

grp2 | .4896411 .1699667 2.88 0.004 .1565124 .8227698

grp3 | .8001383 .1030434 7.77 0.000 .598177 1.0021

grp4 | .6923993 .1199016 5.77 0.000 .4573964 .9274022

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science <- |

read |

grp1 | .370112 .1421434 2.60 0.009 .0915161 .6487079

grp2 | .5359768 .1138689 4.71 0.000 .3127978 .7591559

grp3 | .5117303 .1229149 4.16 0.000 .2708215 .7526391

grp4 | .0790987 .132056 0.60 0.549 -.1797262 .3379236

math |

grp1 | .7413699 .1508776 4.91 0.000 .4456553 1.037084

grp2 | .7482857 .1586025 4.72 0.000 .4374305 1.059141

grp3 | .6460288 .11138 5.80 0.000 .427728 .8643295

grp4 | .6598629 .1066384 6.19 0.000 .4508554 .8688704

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In particular, we are interested in comparing the indirect effects for group 3 with group 4 (.409455 versus .0547679). These are the largest and the smallest of the

indirect effects.

There are two ways we can do this: 1) Using delta method standard errors via nlcom, or 2) using bootstrap standard errors.

Using nlcom

Before we begin using nlcom, let's rerun sem with the coeflegend option to keep the names of the coefficients straight.

sem, coeflegend

Structural equation model Number of obs = 200
Grouping variable = grp Number of groups = 4
Estimation method = ml
Log likelihood = -2051.912

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| Coef. Legend

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Structural |
read <- |
math |
grp1 | .5118412 _b

grp2 | .4896411 _b

grp3 | .8001383 _b

grp4 | .6923993 _b

_cons |

grp1 | 22.44033 _b

grp2 | 25.26262 _b

grp3 | 10.58565 _b

grp4 | 17.2921 _b

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science <- |

read |

grp1 | .370112 _b

grp2 | .5359768 _b

grp3 | .5117303 _b

grp4 | .0790987 _b

math |

grp1 | .5519313 _b

grp2 | .4858494 _b

grp3 | .2365737 _b

grp4 | .605095 _b

_cons |

grp1 | 4.500176 _b

grp2 | 1.473353 _b

grp3 | 10.8461 _b

grp4 | 16.15488 _b

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Variance |

e.read |

grp1 | 61.51621 _b

grp2 | 70.4011 _b

grp3 | 47.59862 _b

grp4 | 46.68944 _b

e.science |

grp1 | 62.14594 _b

grp2 | 41.07736 _b

grp3 | 43.14742 _b

grp4 | 36.6393 _b

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

First, we will reproduce the indirect effects so that we can compare the coefficients and standard errors to those from the estat teffects command. Here is the indirect effect for group 3.

nlcom _b*_b

_nl_1: _b*_b

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| Coef. Std. Err. z P>|z|

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_nl_1 | .409455 .1115931 3.67 0.000 .1907367 .6281734

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And now, the indirect effect for grp 4.

nlcom _b*_b

_nl_1: _b*_b

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| Coef. Std. Err. z P>|z|

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_nl_1 | .0547679 .091926 0.60 0.551 -.1254038 .2349395

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Since these values agree with estat teffects we are finally, we are ready to look at the difference in the two indirect effects.

nlcom (_b*_b) - ///

(_b*_b)

_nl_1: (_b*_b) - (_b*_b)

--

| Coef. Std. Err. z P>|z|

-------------+--

_nl_1 | .3546871 .1445801 2.45 0.014 .0713154 .6380589

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The difference in the indirect effects is .355 and is statistically significant using the delta method standard errors. If you are uncomfortable with the normal theory assumptions behind the delta method, you may want to use the bootstrap method show in the next section.

Using bootstrap

We begin by writing a program, which we are calling bootind, that computes and returns the two indirect effects and the difference between the two. This program must be saved as bootind.ado.

program bootind, rclass

sem (read <- math)(science <- read math), group(grp)

nlcom _b*_b
return scalar ind3 = el(r(b),1,1)

nlcom _b*_b
return scalar ind4 = el(r(b),1,1)

nlcom (_b*_b) - ///
(_b*_b)
return scalar ind3v4 = el(r(b),1,1)
end

We will demonstrate bootind with 500 bootstrap replications. You will probably want to run more replications, maybe a lot more. Also, we will set the random seed so that the results are replicable.

set seed 676767

bootstrap r(ind3) r(ind4) r(ind3v4), reps(500) nodots: bootind

Bootstrap results Number of obs = 200

Replications = 500

command: bootind

_bs_1: r(ind3)

_bs_2: r(ind4)

_bs_3: r(ind3v4)

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| Observed Bootstrap Normal-based

| Coef. Std. Err. z P>|z|

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_bs_1 | .409455 .1059136 3.87 0.000 .2018682 .6170418

_bs_2 | .0547679 .0929578 0.59 0.556 -.1274261 .2369618

_bs_3 | .3546871 .1456614 2.44 0.015 .069196 .6401783

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The confidence intervals shown above are normal-based, so next, we will obtain results with percentile and bias-corrected confidence intervals.

estat boot, percentile bc

Bootstrap results Number of obs = 200

Replications = 500

command: bootind

_bs_1: r(ind3)

_bs_2: r(ind4)

_bs_3: r(ind3v4)

--

| Observed Bootstrap

| Coef. Bias Std. Err.

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_bs_1 | .40945504 .0040702 .10591358 .2073264 .6299226 (P)

| .2047078 .6144838 (BC)

_bs_2 | .05476789 .0025732 .09295781 -.1129886 .2373435 (P)

| -.1134027 .2346437 (BC)

_bs_3 | .35468715 .001497 .14566141 .0743807 .6392108 (P)

| .080749 .6458999 (BC)

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(P) percentile confidence interval

(BC) bias-corrected confidence interval

Neither the percentile nor the bias-corrected confidence intervals for the difference

include zero, so we can conclude that the mediated effects are significantly different between group 2 and group 4.