How can I do moderated mediation with a categorical moderator in Stata?

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Moderated mediation is a statistical technique used to examine the relationship between an independent variable, a mediator, and a dependent variable, while taking into account the influence of a moderator. In Stata, this can be achieved through the use of the "modmed" command. This command allows for the inclusion of a categorical moderator in the mediation analysis, thus allowing for a more comprehensive understanding of how the moderator affects the mediation process. By specifying the appropriate variables and model parameters, Stata can generate results that indicate the direct and indirect effects of the independent variable on the dependent variable, as well as the moderating effect of the categorical moderator. This can provide valuable insights into the underlying mechanisms of the relationship between variables and aid in the interpretation of the results.

How can I do moderated mediation with a categorical moderator in Stata? | Stata FAQ

This page is just an extension of How can I do moderated mediation
in Stata? to include a categorical moderator variable.
We will call that page modmed. If
you are unfamiliar with moderated mediation you should review the modmed
FAQ page before continuing on with this page.

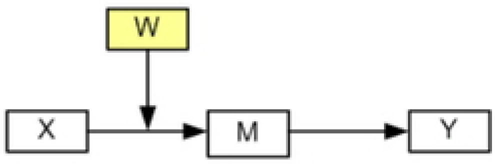
We will to use the same data and the same abbreviated variable names as were used on the
modmed page.

use https://stats.idre.ucla.edu/stat/data/hsbdemo, clear
rename science y /* dependent variable */
rename math x /* independent variable */

rename read m /* mediator variable */
rename prog w /* moderator variable with 3 levels */

The modmed page presented five different models for moderated mediation.
We will select one of them, model 2, to illustrate the use of categorical moderators. The
diagram for model 2 looks like this:

Model 2



Using sureg with manual interactions

For our first pass we will manually create indicator variables and interactions.

tab w, gen(w) // create indicator variables
generate wx2=w2*x // moderator w2 by iv interaction
generate wx3=w3*x // moderator w3 by iv interaction

In model 2 the effect of x on m is what is moderated.
So, the interaction terms need to go in the models for

both m and
y. Thus the sureg command looks like this:

sureg (m x w2 w3 wx2 wx3)(y m x w2 w3 wx2 wx3)

Seemingly unrelated regression

Equation Obs Parms RMSE "R-sq" chi2 P

----

m 200 5 7.493404 0.4632 172.56 0.0000

y 200 6 6.927073 0.5080 206.54 0.0000

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

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

m |

x | .4896411 .1517936 3.23 0.001 .1921311 .787151

w2 | -12.20637 9.068511 -1.35 0.178 -29.98032 5.567587

w3 | -2.822291 9.952575 -0.28 0.777 -22.32898 16.6844

wx2 | .270153 .1735662 1.56 0.120 -.0700305 .6103366

wx3 | .0222002 .2028633 0.11 0.913 -.3754045 .4198048

_cons | 25.26262 7.67478 3.29 0.001 10.22033 40.30491

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

y |

m | .3997664 .0653666 6.12 0.000 .2716503 .5278825

x | .5525436 .1439253 3.84 0.000 .2704552 .8346321

w2 | 5.643216 8.421022 0.67 0.503 -10.86168 22.14812

w3 | -1.079664 9.202235 -0.12 0.907 -19.11571 16.95639

wx2 | -.1860791 .1614174 -1.15 0.249 -.5024513 .1302932

wx3 | -.0157907 .187537 -0.08 0.933 -.3833565 .3517751

_cons | 4.914386 7.284383 0.67 0.500 -9.362742 19.19151

--

Next, we use the nlcom command to compute the conditional indirect effects
for each of the
levels of the moderator variable. For level one multiply each of the interaction terms,
wx2 and wx3 by zero. For level 2, multiply wx2
by one and wx3 by zero. For level 3, just reverse the zeros and ones.
Here is the code:

nlcom (_b+0*_b+0*_b)*_b // for w = 1

_nl_1: (_b+0*_b+0*_b)*_b

--

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

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

_nl_1 | .195742 .0686054 2.85 0.004 .061278 .3302061

----

nlcom (_b+1*_b+0*_b)*_b // for w = 2

_nl_1: (_b+1*_b+0*_b)*_b

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

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

_nl_1 | .3037401 .0599894 5.06 0.000 .186163 .4213173

----

nlcom (_b+0*_b+1*_b)*_b // for w = 3

_nl_1: (_b+0*_b+1*_b)*_b

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

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

_nl_1 | .2046169 .0633558 3.23 0.001 .0804418 .3287921

From these results we see that the indirect effect is strongest when w

= 2 (that is, for the academic program) followed by w = 3 (vocational program) and finally
w = 1 (general program). It is also possible to test whether the indirect
effects for the three levels differ from one another. We will demonstrate this by looking at
the difference between w = 2 and w = 1 (the biggest difference). We do this by subtracting the two nlcom terms.

```
nlcom ((_b+1*_b+0*_b)*_b)-((_b+0*_b+0*_b)*_b)
```

This simplifies to:

```
nlcom (1*_b+0*_b)*_b // w1 vs w2

_nl_1: (1*_b+0*_b)*_b

------------------------------------------------------------------------------
| Coef. Std. Err. z P>|z|
-------------+----------------------------------------------------------------
_nl_1 | .1079981 .0715978 1.51 0.131 -.0323311 .2483272
------------------------------------------------------------------------------
```

In this case the difference in the conditional indirect effects is not statistically significant.

In general, nlcom does a reasonably good job of estimating standard errors and confidence intervals using the delta method. However, the delta method has some fairly strong normality assumptions that may not hold for products of coefficients. Many researchers prefer using the bootstrap to obtain confidence intervals.

Bootstrap confidence intervals

To obtain bootstrap confidence intervals for the conditional indirect effects we begin by writing a program, which we have called bootmmcat and saving it as an ado file called bootmmcat.ado. Here is the program:

```
capture program drop bootmmcat
program bootmmcat, rclass
sureg (m x w2 w3 wx2 wx3)(y m x w2 w3 wx2 wx3)
return scalar w1 = (_b+0*_b+0*_b)*_b
return scalar w2 = (_b+1*_b+0*_b)*_b
```

return scalar w3 = (_b+0*_b+1*_b)*_b

end

Now we can run bootmmcat using the bootstrap command. We will demonstrate this using 500 bootstrap replications. You will want to use more, say 5,000 or 10,000 or more.

bootstrap r(w1) r(w2) r(w3), reps(500) nodots: bootmmcat

Bootstrap results Number of obs = 200

Replications = 500

command: bootmmcat

_bs_1: r(w1)

_bs_2: r(w2)

_bs_3: r(w3)

--

| Observed Bootstrap Normal-based

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

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

_bs_1 | .195742 .075913 2.58 0.010 .0469553 .3445288

_bs_2 | .3037401 .0604079 5.03 0.000 .1853429 .4221374

_bs_3 | .2046169 .0729526 2.80 0.005 .0616324 .3476015

--

By default the bootstrap command produces normal-based confidence
intervals. To get bias corrected or percentile confidence intervals use the
estat boot command.

estat boot, bc percentile

Bootstrap results Number of obs = 200
Replications = 500

command: bootmmcat
_bs_1: r(w1)
_bs_2: r(w2)
_bs_3: r(w3)

--
| Observed Bootstrap
| Coef. Bias Std. Err.
-------------+--
_bs_1 | .19574204 .0015209 .07591302 .0623215 .3492891 (P)

| .0633699 .3669358 (BC)

_bs_2 | .30374014 -.0030653 .06040786 .1904437 .4215902 (P)

| .1981149 .4295833 (BC)

_bs_3 | .20461692 .0020635 .07295263 .0732974 .3612065 (P)

| .0818157 .3720523 (BC)

(P) percentile confidence interval

(BC) bias-corrected confidence interval

All of the examples above used the manually computed indicators and interactions.

The next section shows how to obtain the same results using factor variables.

Using sureg with factor variables

Since this section replicates the above analyses, we will run the commands in a single block
of code.

sureg (m c.x##w)(y m c.x##w)

Seemingly unrelated regression

```
------------------------------------------------------------------
Equation Obs Parms RMSE "R-sq" chi2 P
------------------------------------------------------------------
m 200 5 7.493404 0.4632 172.56 0.0000
y 200 6 6.927073 0.5080 206.54 0.0000
------------------------------------------------------------------

--------------------------------------------------------------------------
| Coef. Std. Err. z P>|z|
-------------+------------------------------------------------------------
m |
x | .4896411 .1517936 3.23 0.001 .1921311 .787151
|
w |
2 | -12.20637 9.068511 -1.35 0.178 -29.98032 5.567587
3 | -2.822291 9.952575 -0.28 0.777 -22.32898 16.6844
|
w#c.x |
2 | .270153 .1735662 1.56 0.120 -.0700305 .6103366
3 | .0222002 .2028633 0.11 0.913 -.3754045 .4198048
|
_cons | 25.26262 7.67478 3.29 0.001 10.22033 40.30491
-------------+------------------------------------------------------------
y |
```

m | .3997664 .0653666 6.12 0.000 .2716503 .5278825
x | .5525436 .1439253 3.84 0.000 .2704552 .8346321
|
w |
2 | 5.643216 8.421022 0.67 0.503 -10.86168 22.14812
3 | -1.079664 9.202235 -0.12 0.907 -19.11571 16.95639
|
w#c.x |
2 | -.1860791 .1614174 -1.15 0.249 -.5024513 .1302932
3 | -.0157907 .187537 -0.08 0.933 -.3833565 .3517751
|
_cons | 4.914386 7.284383 0.67 0.500 -9.362742 19.19151
----

nlcom (_b+0*_b+0*_b)*_b // for w = 1

_nl_1: (_b+0*_b+0*_b)*_b

| Coef. Std. Err. z P>|z|
-------------+--
_nl_1 | .195742 .0686054 2.85 0.004 .061278 .3302061
----

nlcom (_b+1*_b+0*_b)*_b // for w = 2

_nl_1: (_b+1*_b+0*_b)*_b

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

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

_nl_1 | .3037401 .0599894 5.06 0.000 .186163 .4213173

----

nlcom (_b+0*_b+1*_b)*_b // for w = 3

_nl_1: (_b+0*_b+1*_b)*_b

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

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

_nl_1 | .2046169 .0633558 3.23 0.001 .0804418 .3287921

Using the sureg command is not the only way to compute conditional indirect effects.
The next section will show how to do this using the sem command.

Using sem

Since sem does not support factor variables, we will go

back to using
the manually created indicators and interactions.

sem (m

Endogenous variables

Observed: m y

Exogenous variables

Observed: x w2 w3 wx2 wx3

Fitting target model:

Iteration 0: log likelihood = -3316.2503
Iteration 1: log likelihood = -3316.2503

Structural equation model Number of obs = 200
Estimation method = ml
Log likelihood = -3316.2503

| OIM
| Coef. Std. Err. z P>|z|
-------------+--

Structural |

m chi2 = .

To see the names of each of the coefficients, just use the coeflegend option with sem.

sem, coeflegend

Structural equation model Number of obs = 200
Estimation method = ml
Log likelihood = -3316.2503

--
| Coef. Legend
-------------+--
Structural |
m chi2 = .

As you can see, the names of the coefficients are the same as we used with the sureg command. So, the nlcom commands would be exactly the same.

nlcom (_b+0*_b+0*_b)*_b // for w = 1

_nl_1: (_b+0*_b+0*_b)*_b

--

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

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

_nl_1 | .195742 .0686054 2.85 0.004 .061278 .3302061

--

nlcom (_b+1*_b+0*_b)*_b // for w = 2

_nl_1: (_b+1*_b+0*_b)*_b

--

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

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

_nl_1 | .3037401 .0599894 5.06 0.000 .186163 .4213173

--

nlcom (_b+0*_b+1*_b)*_b // for w = 3

_nl_1: (_b+0*_b+1*_b)*_b

--

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

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

_nl_1 | .2046169 .0633558 3.23 0.001 .0804418 .3287921

The methods given on this page can be adapted to any of the other four models for moderated mediation found on the modmed page.