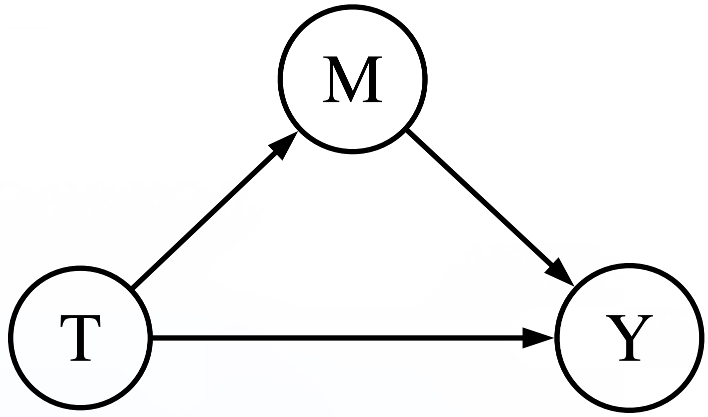
New in STATA 18

Causal mediation analysis

Want to better understand a causal relationship? Causal mediation analysis explains these relationships by decomposing a treatment effect into a direct effect of the treatment on the outcome and an indirect effect through another variable, the mediator.

With Stata's new **mediate** command, you can fit causal mediation models for a variety of outcome and mediator model combinations.



- Linear, logit, probit, Poisson, and exponential-mean models
- Direct effects, indirect effects, total effects, proportion mediated, and potential-outcome means
- Continuous, binary, and count outcomes
- Continuous, binary, and count mediators
- Binary, multivalued, and continuous treatments

Fit the model

Suppose we wish to evaluate the effect of physical exercise on self-perceived well-being and investigate potential causal mechanisms. Perhaps exercising causes an increase in certain hormones in the human body, which in turn affect perceptions of well-being. To explore these relationships, we use a causal mediation model.

We specify the outcome, the mediator, and the treatment variable.

```
. mediate (wellbeing) (bonotonin) (exercise)
```

The natural indirect effect (NIE) of 9.8 is an estimate of the effect of exercise on well-being through production of the fictional hormone bonotonin. The natural direct effect (NDE) of 2.9 is an estimate of the effect of exercise on well-being through mechanisms other than bonotonin. Together, they sum to a total effect (TE) of exercise on well-being.

Perhaps we want to know the effect of exercise on well-being if we could control the bonotonin level. To estimate the controlled direct effect with bonotonin set to 10, we type

```
. estat cde, mvalue(10)
```

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```
. mediate (wellbeing) (bonotonin) (exercise)

Causal mediation analysis                              Number of obs = 2,000

Outcome model:     Linear
Mediator model:    Linear
Mediator variable: bonotonin
Treatment type:    Binary

------------------------------------------------------------------------------
                     |               Robust
           wellbeing | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
---------------------+--------------------------------------------------------
NIE                  |
            exercise |
 (Exercise vs Control)|   9.799821   .3943251    24.85   0.000     9.026958    10.57268
---------------------+--------------------------------------------------------
NDE                  |
            exercise |
 (Exercise vs Control)|   2.891453   .2304278    12.55   0.000     2.439823    3.343083
---------------------+--------------------------------------------------------
TE                   |
            exercise |
 (Exercise vs Control)|   12.69127   .4005941    31.68   0.000     11.90612    13.47642
------------------------------------------------------------------------------
Note: Outcome equation includes treatment-mediator interaction.
```

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Include covariates

We can control for confounders by including them in the model for the outcome, mediator, or both.

```
. mediate (wellbeing basewell age i.hstatus)
          (bonotonin i.gender i.hstatus)
          (exercise)

Causal mediation analysis                         Number of obs = 2,000

Outcome model:     Linear
Mediator model:    Linear
Mediator variable: bonotonin
Treatment type:    Binary

------------------------------------------------------------------------------
                     |               Robust
           wellbeing | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
---------------------+--------------------------------------------------------
NIE                  |
            exercise |
(Exercise vs Control)|   9.718811    .369158    26.33   0.000     8.995274    10.44235
---------------------+--------------------------------------------------------
NDE                  |
            exercise |
(Exercise vs Control)|   3.092069   .1676971    18.44   0.000     2.763389     3.42075
---------------------+--------------------------------------------------------
TE                   |
            exercise |
(Exercise vs Control)|   12.81088   .3723542    34.41   0.000     12.08108    13.54068
------------------------------------------------------------------------------
Note: Outcome equation includes treatment-mediator interaction.
```

When controlling for covariates, the estimated total effect is 12.8. If everyone in the population exercised, well-being would be, on average, 12.8 points higher than if no one exercised. Of this, a 9.7-point increase is due to the mediating effect via bonotonin, and a 3.1-point increase is due to other mechanisms. We could type **estat proportion** to learn that the effect via bonotonin is 76% of the total effect.

Alternative statistics

Add the **all** option to report alternative direct effects, indirect effects, and potential-outcome means.

```
. mediate (wellbeing) (bonotonin) (exercise), all

Causal mediation analysis                         Number of obs = 2,000

------------------------------------------------------------------------------
                     |               Robust
           wellbeing | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
---------------------+--------------------------------------------------------
POmeans              |
                Y0M0 |   57.11317   .2753201   207.44   0.000     56.57355    57.65278
                Y1M0 |   60.00462   .3157888   190.02   0.000     59.38569    60.62356
                Y0M1 |   66.68199   .3258477   204.64   0.000     66.04334    67.32064
                Y1M1 |   69.80444   .2898927   240.79   0.000     69.23626    70.37262
---------------------+--------------------------------------------------------
NIE                  |
            exercise |
(Exercise vs Control)|   9.799821   .3943251    24.85   0.000     9.026958    10.57268
---------------------+--------------------------------------------------------
NDE                  |
            exercise |
(Exercise vs Control)|   2.891453   .2304278    12.55   0.000     2.439823    3.343083
---------------------+--------------------------------------------------------
PNIE                 |
            exercise |
(Exercise vs Control)|   9.568827   .3884522    24.63   0.000     8.807475    10.33018
---------------------+--------------------------------------------------------
TNDE                 |
            exercise |
(Exercise vs Control)|   3.122447   .2418591    12.91   0.000     2.648412    3.596482
---------------------+--------------------------------------------------------
TE                   |
            exercise |
(Exercise vs Control)|   12.69127   .4005941    31.68   0.000     11.90612    13.47642
------------------------------------------------------------------------------
```

The pure natural indirect effect (PNIE) and total natural direct effect (TNDE) are alternative decompositions of the total effect. Potential-outcome means are the expected values of the outcome under specific conditions. For example, the Y0M0 of 57.1 is the expected well-being if no one exercises.

Alternative models

By default, **mediate** assumes a linear model for the outcome and mediator and a categorical treatment variable.

For a binary outcome or mediator, add the **logit** or **probit** option.

```
. mediate (y1 x1 x2, logit)
          (m1 x1 x3, logit)
          (treat)
```

Then, type **estat or** or **estat rr** to calculate effects on the odds-ratio or risk-ratio scale.

For count variables, use the **poisson** option.

```
. mediate (y2 x1 x2, poisson)
          (m2 x1 x3, logit)
          (treat)
```

Then type **estat irr** to calculate effects on the incidence-rate–ratio scale.

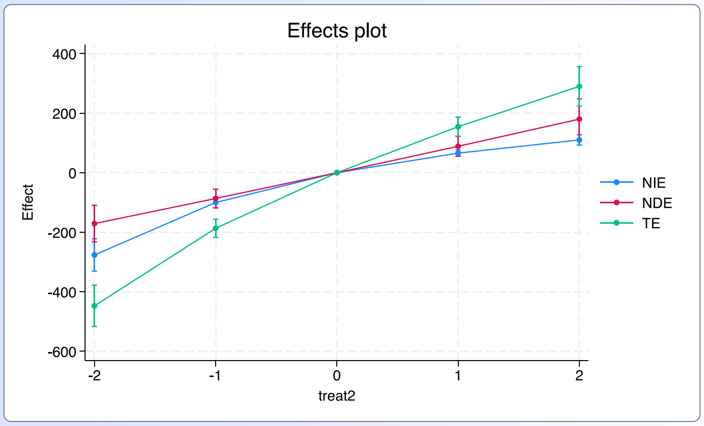
For exponential-mean models, use the **expmean** option.

```
. mediate (y3 x1 x2, expmean)
          (m1 x1 x3, probit)
          (treat)
```

When the treatment is continuous, we specify the **continuous()** suboption to indicate control and treatment levels of interest

```
. mediate (y x1 x2)
          (m x1 x3)
          (treat2, continuous(0 -2 -1 1 2))
```

We can visualize the treatment effects at each value of the treatment variable we specified with **estat effectsplot**.



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