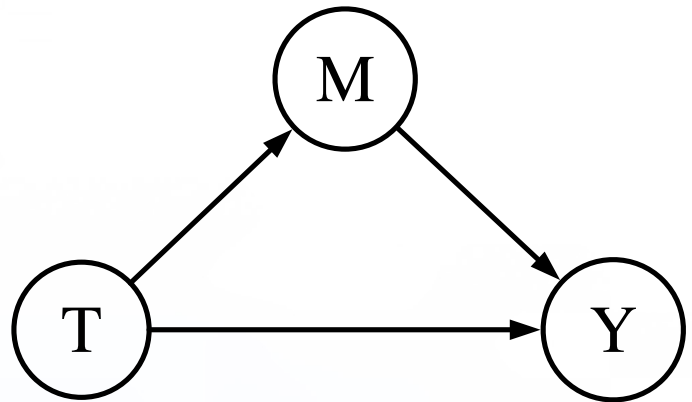


Causal mediation analysis

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)
```

Viewer - view cma.sml

File Edit History Help

view cma.sml X

. mediate (wellbeing) (bonotonin) (exercise) Dialog ▾ Also see ▾ Jump to ▾

Causal mediation analysis Number of obs = 2,000

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

	wellbeing	Robust		z	P> z	[95% conf. interval]	
		Coefficient	std. err.				
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.

CAP NUM INS

Include covariates

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

Viewer - view cma.sml

```

+
. 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
  
```

	wellbeing	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]
NIE (Exercise vs Control)	exercise	9.718811	.369158	26.33	0.000	8.995274 10.44235
NDE (Exercise vs Control)	exercise	3.092069	.1676971	18.44	0.000	2.763389 3.42075
TE (Exercise vs Control)	exercise	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.

Viewer - view cma.sml

```

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

Causal mediation analysis
Number of obs = 2,000
  
```

	wellbeing	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]
PMeans	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 vs Control)	exercise	9.799821	.3943251	24.85	0.000	9.026958 10.57268
NDE (Exercise vs Control)	exercise	2.891453	.2304278	12.55	0.000	2.439823 3.343083
PNIE (Exercise vs Control)	exercise	9.568827	.3884522	24.63	0.000	8.807475 10.33018
TNDE (Exercise vs Control)	exercise	3.122447	.2418591	12.91	0.000	2.648412 3.596482
TE (Exercise vs Control)	exercise	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**.

