mediate intro — Introduction to causal mediation analysis

Description Remarks and examples References Also see

Description

Causal inference aims to estimate the causal effect of a treatment on an outcome. Causal mediation analysis further explores the causal effect by evaluating how that effect may arise. In particular, the total effect can be decomposed into a direct effect and one or more indirect effects. An indirect effect is an effect in which the treatment leads to a change in an intervening variable, a mediator, and that change then leads to a change in an outcome. Causal mediation analysis explores whether and to what extent the effect of a treatment on an outcome is due to a change in the mediator.

In this entry, we provide a conceptual introduction to causal mediation analysis and the corresponding research process. We also introduce the `mediate` command for fitting causal mediation models.

For syntax and further details on fitting causal mediation models with one mediator, see [CAUSAL] **mediate**. For syntax and further details on fitting causal mediation models with two mediators, see [CAUSAL] **mediate multiple**.

Remarks and examples

Remarks are presented under the following headings:

Introduction

Causal inference is an essential goal in many research areas and aims at identifying and quantifying causal effects. For example, we might wish to find out whether physical exercise leads to an improvement in self-perceived well-being, and if so, to what extent. Causality in this context typically means that there is some cause T that has an effect on some outcome Y. We could visualize this relation with a simple causal diagram:

Figure 1

If T is a measure of exercise and Y is well-being, then under certain assumptions, we could use the above causal model to identify the total effect of exercise on well-being (by means of a randomized controlled trial, for instance). However, a question that we cannot answer empirically with our simple causal model is why exercise may increase well-being. Perhaps exercising causes an increase in certain chemicals or hormones in the human body, which in turn affects perceptions of well-being. To assess such intermediary effects, we need to expand our simple causal model by adding variables that lie on the causal pathway between T and Y:

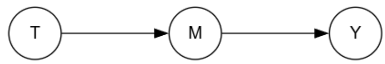


Figure 2

Suppose that, in our exercise example, the variable M represents the production of a certain chemical in the human body. With this new model, we now hypothesize that exercising leads to the production of this chemical, which in turn leads to an increase in well-being. However, it might be unrealistic to assume that the effect of exercise on well-being hinges exclusively on the production of that chemical. Perhaps we would like to allow for the possibility that exercise has an effect on well-being beyond its path through the mediating variable, and so a better model might be

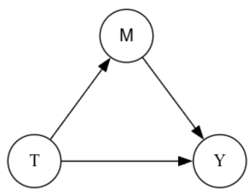


Figure 3

Here we include a direct path from T to Y in addition to the indirect path of T to Y via M. In other words, we assume that exercise produces a particular chemical that affects well-being, but we also allow for the possibility of a direct effect of exercise on well-being that is not related to the chemical. This is the classical mediation model that decomposes the total effect into a direct and an indirect effect. Causal mediation analysis aims to identify these direct and indirect effects and give them a causal interpretation.

Causal mediation analysis can extend beyond this basic model. We could have multiple mediators of interest. For instance, we could also hypothesize that increasing exercise leads to increased strength, which in turn leads to an increase in well-being. Again, we assume that exercise may affect well-being in ways other than changes in the chemical and in strength. Our model now can be represented by the following diagram in which M_1 represents the chemical and M_2 represents strength.

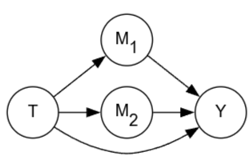


Figure 4

We can now decompose the total effect into a direct effect and two indirect effects.

In figure 4, the mediators are known as parallel mediators. Neither mediator is assumed to predict the other. Perhaps we also hypothesize that the change in the chemical can lead to a change in strength. In this case, the mediators are known as sequential mediators. In our diagram, we now add an arrow from M_1 to M_2.

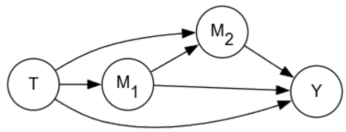


Figure 5

Here there are four path-specific effects of interest: the direct effect from T to Y (that is, the effect of T on Y not mediated by either M_1 or M_2); one effect through M_1 alone; one through M_2 alone; and one through both M_1 and M_2. These four effects combined will sum to the total causal effect.

In each of these situations, we can use causal mediation analysis to estimate the direct and indirect effects of interest to better understand the effect of T on Y.

Approaches to mediation analysis

Mediation analysis can be performed in a variety of ways. For the one mediator case, the classical approach of Baron and Kenny (1986) fits two linear regression models, one for M and one for Y, and estimates direct, indirect, and total effects as functions of the coefficients. Estimation can be simplified by fitting the models for M and Y simultaneously via structural equation modeling as discussed in [SEM] **Example 42g**. In Stata, you can use `sem` to fit linear models for the outcome and mediator, and you can then use `estat teffects` to obtain a decomposition of direct and indirect effects based on the results from `sem`. Similarly, models with two parallel or sequential mediators can be fit with `sem`, and `estat teffects` and `nlcom` can be used to estimate direct and indirect effects. Note that this classical approach relies on the specification of a particular model at the outset of the process.

Another approach to mediation analysis is based on the potential-outcomes framework. The potential outcomes are values of the outcome that would be obtained under different conditions, such as when the treatment occurs. Differences in potential outcomes yield direct, indirect, and total effects of interest. This is the approach typically referred to as causal mediation analysis and is the one implemented in `mediate`.

The causal mediation framework allows much flexibility. In this framework, it is common to allow the mediator and the treatment to interact; thus, we do not assume that the effect of a mediator on the outcome is the same for the treated and untreated groups. The total effect of the treatment on the outcome can be decomposed into direct and indirect effects in multiple ways, and the researcher can study the decomposition or decompositions that answer the research questions of interest. The effects are defined in a model-free manner, so the researcher can select an estimation method that is appropriate for his or her data and then compute estimates of the effects of interest.

When the outcome and the mediators are modeled using linear regression and there is no treatment–mediator interaction (and no mediator–mediator interaction in the two-mediator case), the classical approach and causal mediation via the potential-outcomes framework will lead to the same results.

Workflow for causal mediation

The general workflow for researchers performing causal mediation analysis is as follows:

1. Specify your research question.
2. Identify the treatment, mediators, and outcome to be analyzed.
3. Determine which effect decomposition or decompositions can be used to answer your research question.
4. Evaluate whether assumptions for causal interpretation are appropriate.
5. Select a method for estimating the causal effects of interest.
6. Interpret the results.

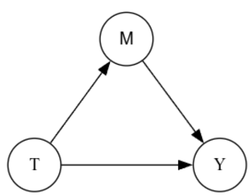
In our introductory discussion, we provided simple examples of step 2 by using exercise, chemical production, strength, and well-being. Below, we will briefly provide a conceptual introduction to the remaining steps.

Potential outcomes, effects, and decompositions

Causal mediation analysis allows us to estimate a variety of effects that are defined in terms of potential-outcome means. Here we discuss the potential-outcome means that can be estimated in both the one-mediator and two-mediator cases, and we show how different effects can be estimated from these to answer a variety of research questions. To explore these concepts, we will use a simple example and demonstrate how to use the `mediate` command.

One mediator

With one mediator, we are interested in decomposing the total effect of a treatment on the outcome into the indirect effect through a mediator and the direct effect.



To explore causal mediation for this case, we use a treatment variable `t`, a mediator variable `m`, and an outcome variable `y`.

Causal mediation relies on estimating the total, indirect, and direct effects of interest from potential-outcome means. Therefore, we will first consider the four potential-outcome means. To obtain these with `mediate`, we specify our outcome, mediator, and treatment in parentheses followed by the `pomeans` option.

```
. mediate (y) (m) (t), pomeans

Iteration 0:  EE criterion = 2.804e-27
Iteration 1:  EE criterion = 1.878e-28

Causal mediation analysis                              Number of obs = 2,000

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

------------------------------------------------------------------------------
             |               Robust
           y | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
POmeans      |
        Y0M0 |   31.04239   .2603784   119.22   0.000     30.53205    31.55272
        Y1M0 |    29.7409    .242952   122.41   0.000     29.26473    30.21708
        Y0M1 |   26.95702   .1644953   163.88   0.000     26.63462    27.27943
        Y1M1 |    26.2634   .1281546   204.94   0.000     26.01222    26.51458
------------------------------------------------------------------------------
Note: Outcome equation includes treatment-mediator interaction.
```

Here the first potential-outcome mean, labeled `Y0M0`, is the population-average value of the outcome that would be expected if everyone was untreated. In this notation, `Y0` implies it is the value of `y` when the treatment is set to 0, and `M0` implies the mediator is set to its value that would occur when the treatment is 0. Similarly, the last potential-outcome mean, labeled `Y1M1`, is the population-average value of the outcome that would be expected if everyone was given the treatment.

The potential-outcome means labeled `Y1M0` and `Y0M1` are known as cross-world potential-outcome means. `Y1M0` is the expected value of the outcome when everyone is treated but counterfactually experiences the value of the mediator associated with being untreated. `Y0M1` is the expected value of the outcome when everyone is untreated but counterfactually experiences the value of the mediator associated with being treated.

From these four potential-outcome means, we can estimate the total, indirect, and direct effects. These effects are reported by `mediate` by default.

```
. mediate (y) (m) (t)
Iteration 0:  EE criterion = 2.804e-27
Iteration 1:  EE criterion = 1.262e-28
Causal mediation analysis                                Number of obs = 2,000
Outcome model:     Linear
Mediator model:    Linear
Mediator variable: m
Treatment type:    Binary

------------------------------------------------------------------------------
             |               Robust
           y | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
NIE          |
           t |
  (Yes vs No)|  -3.477502   .2286525   -15.21   0.000    -3.925653   -3.029352
-------------+----------------------------------------------------------------
NDE          |
           t |
  (Yes vs No)|  -1.301482   .1701042    -7.65   0.000     -1.63488   -.9680837
-------------+----------------------------------------------------------------
TE           |
           t |
  (Yes vs No)|  -4.778984    .287326   -16.63   0.000    -5.342133   -4.215836
------------------------------------------------------------------------------
Note: Outcome equation includes treatment-mediator interaction.
```

The total effect, labeled `TE`, is the difference in potential-outcome means when everyone is treated versus when everyone is untreated (`Y1M1 - Y0M0`). It has the same interpretation as an average treatment effect that is commonly reported with other causal inference methods. We expect the average of `y` to be 4.78 less in the population when everyone is treated versus when no one is treated.

What is unique to causal mediation is the ability to better understand this effect in terms of the mediator. The value labeled `NIE` is the estimated natural indirect effect, sometimes called the total natural indirect effect, which is the portion of the total effect that can be attributed to a change in `t` leading to a change in `m`, which in turn leads to a change in `y`. The value labeled `NDE` is the estimated natural direct effect, sometimes called the pure natural direct effect, which is the portion of the total effect not attributed to mediation through `m`. The total effect is the sum of the natural indirect effect and the natural direct effect, and we can see that in this case, the indirect effect is larger (in absolute value) than the direct effect, accounting for over half of the total effect.

Causal mediation allows for the effect of the mediator to differ for treated and untreated groups by allowing for interaction between the treatment and mediator in the model for the outcome, as noted at the bottom of this output. This leads to two possible ways to decompose the total effect into direct and indirect effects. The decomposition above includes the interaction effect in the indirect effect and isolates the direct effect. Nguyen, Schmid, and Stuart (2021) recommend using this decomposition when the researcher assumes a direct effect exists and is questioning whether any mediation effect via `m` exists.

The second decomposition can be obtained as follows:

```
. mediate (y) (m) (t), pnie tnde te
Iteration 0:  EE criterion = 2.804e-27
Iteration 1:  EE criterion = 1.036e-28
Causal mediation analysis                              Number of obs = 2,000
Outcome model:     Linear
Mediator model:    Linear
Mediator variable: m
Treatment type:    Binary
```

y	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
PNIE						
t						
(Yes vs No)	-4.085363	.2791863	-14.63	0.000	-4.632558	-3.538168
TNDE						
t						
(Yes vs No)	-.6936208	.1656556	-4.19	0.000	-1.0183	-.3689417
TE						
t						
(Yes vs No)	-4.778984	.287326	-16.63	0.000	-5.342133	-4.215836

```
Note: Outcome equation includes treatment-mediator interaction.
```

Here the value labeled `PNIE` is the estimated pure natural indirect effect, and the value labeled `TNDE` is the estimated total natural direct effect. These two sum to the same total effect that we obtained previously. This decomposition includes the interaction effect in the direct effect and isolates the indirect effect. Nguyen, Schmid, and Stuart (2021) recommend using this decomposition when the researcher assumes that there is a mediating effect via `m` and is questioning whether any additional effects exist.

When the research question does not make a prior assumption about a direct or indirect effect, Nguyen, Schmid, and Stuart (2021) note that both of these decompositions can be reported to characterize the mediating effects.

Researchers may also want to investigate what the direct effect would be if the mediator is set to a specific value of interest. The controlled direct effect provides this information and can be estimated by using `estat cde` after `mediate`.

```
. estat cde, mvalue(5)
Controlled direct effect                               Number of obs = 2,000
Mediator variable: m
Mediator value = 5
```

	CDE	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
t						
(Yes vs No)	-2.876864	.4969117	-5.79	0.000	-3.850793	-1.902935

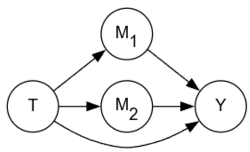
Here we estimate the effect of `t` on `y` when `m` is set to 5.

Causal inference based on estimates like those shown above requires a number of assumptions. In particular, we assume that there is no unobserved confounding in the treatment–outcome relationship, in the mediator–outcome relationship, or in the treatment–mediator relationship. In addition, we assume there are no confounders in the mediator–outcome relationship that are caused by the treatment.

In this section, we provided a preview of the types of research questions, the related effects that can be estimated, the assumptions, and the syntax of the `mediate` command that can be used to fit models to perform causal mediation analysis with one mediator. `mediate` also allows for specifying covariates in the outcome and mediator models and for modeling mediators and outcomes that are continuous, binary, or count. For more conceptual and technical details, command syntax, and worked examples using `mediate` with one mediator, see [CAUSAL] **mediate** and the references provided there.

Two parallel mediators

When we evaluate two mediators in causal mediation analysis, we can decompose the total effects into a direct effect and indirect effects via each mediator. When two mediators are parallel, there are three pathways of interest from the treatment to the outcome.



We will extend our example above to include two mediators, `m1` and `m2`, as we explore the potential-outcomes framework, effects of interest, and the `mediate` command with two parallel mediators.

We first consider the potential-outcome means when mediators are parallel and when we allow for interactions between the treatment and each of the mediators as well as an interaction between the two mediators. This is the most flexible version of the causal mediation model with parallel mediators. We specify the outcome, mediators, and treatment and request potential-outcome means in the `mediate` command similarly to the specification for the one-mediator case. We also add the `tinteraction` and `minteraction` options to include the interactions.

```
. mediate (y) (m2) (m1) (t), tinteraction minteraction pomeans
Iteration 0:  EE criterion = 2.526e-26
Iteration 1:  EE criterion = 8.897e-29
Causal mediation analysis                             Number of obs = 2,000
Mediation type: Parallel
Mediator 1:     m1
Mediator 2:     m2
Treatment type: Binary
```

y	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
POmeans						
000	31.64364	.3251299	97.33	0.000	31.0064	32.28088
001	31.4691	.4037414	77.94	0.000	30.67778	32.26041
010	28.3664	.1809759	156.74	0.000	28.01169	28.7211
011	28.07937	.16393	171.29	0.000	27.75807	28.40066
100	29.89799	.3377696	88.52	0.000	29.23597	30.56
101	29.66508	.372723	79.59	0.000	28.93455	30.3956
110	26.91666	.2504554	107.47	0.000	26.42578	27.40755
111	26.44074	.1378333	191.83	0.000	26.1706	26.71089

```
Note: Outcome equation includes treatment-mediator interactions and
      mediator-mediator interaction.
```

While we had only four potential-outcome means with one mediator, we now have eight. The first one, labeled `000`, is the population-average value of `y` that would be expected if everyone was untreated. The last one, labeled `111`, is the population-average value of `y` that would be expected if everyone was treated. In between, we have cross-world potential outcomes that are similar to those in the one mediator case. The first number corresponds to `y`, the second to `m1`, and the third to `m2`, where `0` corresponds to untreated and `1` corresponds to treated in each of these positions. So the potential-outcome mean labeled `001` is the expected value of `y` when everyone is untreated and experiences the value of `m1` associated with being untreated and the value of `m2` associated with being treated. The other cross-world potential-outcome means can be interpreted similarly.

From these potential-outcome means, we can estimate the total, indirect, and direct effects.

```
. mediate (y) (m2) (m1) (t), tinteraction minteraction
Iteration 0:  EE criterion = 2.526e-26
Iteration 1:  EE criterion = 1.137e-28
Causal mediation analysis                                 Number of obs = 2,000
Mediation type: Parallel
Mediator 1:     m1
Mediator 2:     m2
Treatment type: Binary
```

y	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
NDE						
00	-1.745654	.1767601	-9.88	0.000	-2.092097	-1.39921
10	-1.449735	.2693148	-5.38	0.000	-1.977582	-.9218876
01	-1.804018	.2952766	-6.11	0.000	-2.38275	-1.225287
11	-1.638622	.139265	-11.77	0.000	-1.911576	-1.365667
NIE1						
00	-3.277243	.3619214	-9.06	0.000	-3.986596	-2.56789
10	-2.981325	.3508021	-8.50	0.000	-3.668884	-2.293765
01	-3.389729	.3789566	-8.94	0.000	-4.132471	-2.646988
11	-3.224333	.4005567	-8.05	0.000	-4.00941	-2.439256
NIE2						
00	-.174545	.1703176	-1.02	0.305	-.5083614	.1592713
10	-.2329098	.2139202	-1.09	0.276	-.6521856	.186366
01	-.2870311	.1642122	-1.75	0.080	-.6088811	.0348188
11	-.4759182	.2112993	-2.25	0.024	-.8900573	-.0617791
TE						
t						
(Yes vs No)	-5.202896	.3531395	-14.73	0.000	-5.895037	-4.510756

```
Note: Outcome equation includes treatment-mediator interactions and
      mediator-mediator interaction.
```

The total effect, `TE`, is interpreted just like the total effect in the one-mediator case. However, we now can estimate four natural direct effects and four natural indirect effects through each mediator. The natural direct effects (`NDE`) here range from −1.45 to −1.80. The first of these, labeled `00`, is the estimated direct effect when both mediators are at their values associated with being untreated. The `NIE1` section reports natural indirect effects through the `m1` mediator, which range from −2.98 to −3.39. The `00` indirect effect is the effect via `m1` if everyone was untreated and if `m2` is set to its value associated with being untreated. Other indirect effects are interpreted similarly. The `NIE2` section reports natural indirect effects through the `m2` mediator, which range from −0.17 to −0.48. From these results, there are six possible ways to decompose the total effect into a direct effect, an indirect effect through `m1`, and an indirect effect through `m2`. While we do not show all of these decompositions in this introduction, reviewing all the reported effects, we see that the indirect effect through `m1` is larger than both the direct effect and the indirect effect through `m2`.

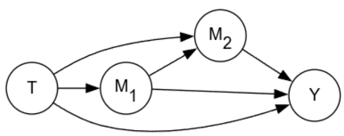
In addition to the natural direct and indirect effects, we can also estimate controlled direct effects, as we did in the case of one mediator. This estimate is useful when the research question asks what the direct effect would be when the mediators are set to specific values.

```
. estat cde, mvalue(m1=3 m2=5)

Controlled direct effect                                Number of obs = 2,000

Mediator variables: m1 m2
Mediator values:
  m1 = 3
  m2 = 5

------------------------------------------------------------------------------
             |              Delta-method
             |        CDE     std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
           t |
  (Yes vs No) |  -1.485701    .7919253    -1.88   0.061    -3.037846    .0664441
------------------------------------------------------------------------------
```

Here we estimate the direct effect of `t` on `y` when setting `m1` to 3 and `m2` to 5.

Two sequential mediators

When two mediators are sequential, there are now four pathways that may be of interest from the treatment to the outcome.



Continuing with our example above, we have now introduced a path from `m1` to `m2`, which means we can estimate an indirect effect that goes through both `m1` and `m2` in addition to the indirect effect through `m1` alone and the indirect effect through `m2` alone.

With this additional causal pathway, there are more potential-outcome means that can be estimated. The most flexible version of a model for sequential mediators allows for interactions between the treatment and mediators and between the mediators in the outcome equation and allows for an interaction between the treatment and the first mediator in the equation for the second mediator. Here we estimate all the potential-outcome means in this most flexible case. In the `mediate` command, we include the `sequential` option to specify that the mediators are sequential and the `meqtinteraction` option to include the interaction in the mediator equation.

```
. mediate (y) (m2) (m1) (t), sequential tinteraction minteraction
> meqtinteraction pomeans

Iteration 0:  EE criterion = 6.373e-21
Iteration 1:  EE criterion = 2.656e-28

Causal mediation analysis                              Number of obs = 2,000

Mediation type: Sequential
Mediator 1:     m1
Mediator 2:     m2
Treatment type: Binary
```

y	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
POmeans						
0000	31.30634	.2935023	106.66	0.000	30.73109	31.8816
0001	31.20478	.3270818	95.40	0.000	30.56371	31.84584
0010	31.2244	.3084594	101.23	0.000	30.61984	31.82897
0011	31.11898	.3576589	87.01	0.000	30.41798	31.81997
0100	28.0291	.1958977	143.08	0.000	27.64515	28.41305
0101	27.86208	.1574547	176.95	0.000	27.55347	28.17068
0110	27.90262	.1665546	167.53	0.000	27.57618	28.22906
0111	27.72925	.1619862	171.18	0.000	27.41176	28.04673
1000	29.16931	.2600319	112.18	0.000	28.65966	29.67896
1001	29.03378	.2511767	115.59	0.000	28.54148	29.52608
1010	29.04938	.2429515	119.57	0.000	28.5732	29.52556
1011	28.9087	.2744599	105.33	0.000	28.37077	29.44663
1100	26.18799	.2941772	89.02	0.000	25.61141	26.76456
1101	25.91105	.2332539	111.09	0.000	25.45388	26.36822
1110	25.97183	.2590678	100.25	0.000	25.46407	26.47959
1111	25.68436	.2425794	105.88	0.000	25.20892	26.15981

```
Note: Outcome equation includes treatment-mediator interactions and
      mediator-mediator interaction, and mediator 2 equation includes
      treatment-mediator interaction.
```

This produces 16 potential-outcome means. Again the first one, labeled 0000, is the population-average value of y that would be expected if everyone was untreated. The last one, labeled 1111, is the population-average value of y that would be expected if everyone was treated. The difference in these two leads to the total effect. The remaining potential-outcome means correspond to various cross-world potential outcomes. From these 16 potential-outcome means, we can estimate 8 of each type of direct and indirect effects.

```
. mediate (y) (m2) (m1) (t), sequential tinteraction minteraction
> meqtinteraction
Iteration 0:  EE criterion = 6.373e-21
Iteration 1:  EE criterion = 5.935e-28
Causal mediation analysis                          Number of obs = 2,000
Mediation type: Sequential
Mediator 1:     m1
Mediator 2:     m2
Treatment type: Binary

------------------------------------------------------------------------------
             |               Robust
           y | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
NDE          |
         000 |   -2.137034   .1755708   -12.17   0.000    -2.481146   -1.792921
         100 |   -1.841115   .2914441    -6.32   0.000    -2.412335   -1.269895
         010 |   -2.175025   .1867005   -11.65   0.000    -2.540951   -1.809098
         001 |   -2.170996   .1970605   -11.02   0.000    -2.557228   -1.784765
         110 |    -1.93079   .2240868    -8.62   0.000    -2.369992   -1.491587
         101 |   -1.951029   .1944125   -10.04   0.000     -2.33207   -1.569987
         011 |   -2.210278    .284549    -7.77   0.000    -2.767984   -1.652573
         111 |   -2.044882   .1971614   -10.37   0.000    -2.431311   -1.658453
-------------+----------------------------------------------------------------
NIE1         |
         000 |   -3.277243   .3619214    -9.06   0.000    -3.986596    -2.56789
         100 |   -2.981325   .3508021    -8.50   0.000    -3.668884   -2.293765
         010 |   -3.321785   .3659441    -9.08   0.000    -4.039022   -2.604548
         001 |   -3.342699   .3726794    -8.97   0.000    -4.073137   -2.612261
         110 |    -3.07755   .3644594    -8.44   0.000    -3.791877   -2.363223
         101 |   -3.122732   .3817002    -8.18   0.000     -3.87085   -2.374613
         011 |   -3.389729   .3789566    -8.94   0.000    -4.132471   -2.646988
         111 |   -3.224333   .4005567    -8.05   0.000     -4.00941   -2.439256
-------------+----------------------------------------------------------------
NIE2         |
         000 |   -.0819393   .0646655    -1.27   0.205    -.2086815    .0448028
         100 |   -.1199303   .0962299    -1.25   0.213    -.3085375    .0686768
         010 |    -.126481   .0623618    -2.03   0.043    -.2487078   -.0042542
         001 |   -.0858009    .068813    -1.25   0.212    -.2206718      .04907
         110 |   -.2161557   .0956439    -2.26   0.024    -.4036142   -.0286971
         101 |   -.1250831    .104926    -1.19   0.233    -.3307343    .0805681
         011 |   -.1328312   .0670555    -1.98   0.048    -.2642576   -.0014048
         111 |   -.2266847   .1099928    -2.06   0.039    -.4422665   -.0111028
-------------+----------------------------------------------------------------
NIE12        |
         000 |    -.101568    .100049    -1.02   0.310    -.2976605    .0945245
         100 |   -.1355305   .1244552    -1.09   0.276    -.3794582    .1083972
         010 |   -.1670238   .0977036    -1.71   0.087    -.3585193    .0244717
         001 |   -.1054296   .1019476    -1.03   0.301    -.3052432    .0943841
         110 |   -.2769374   .1246697    -2.22   0.026    -.5212856   -.0325893
         101 |   -.1406833   .1288855    -1.09   0.275    -.3932943    .1119277
         011 |   -.1733739   .0984035    -1.76   0.078    -.3662413    .0194934
         111 |   -.2874664   .1298441    -2.21   0.027    -.5419561   -.0329768
-------------+----------------------------------------------------------------
TE           |
           t |
(Yes vs No)  |    -5.62198    .452873   -12.41   0.000    -6.509595   -4.734365
------------------------------------------------------------------------------
Note: Outcome equation includes treatment-mediator interactions and
      mediator-mediator interaction, and mediator 2 equation includes
      treatment-mediator interaction.
```

The total effect is estimated to be −5.62. The natural direct effects are reported in the NDE section and range from −1.84 to −2.21. The natural indirect effects through m1 only are reported in the NIE1 section and range from −2.98 to −3.39. The natural indirect effects through m2 only are reported in the NIE2 section and range from −0.08 to −0.23. The natural indirect effects through both m1 and m2 are reported in the NIE12 section and range from −0.10 to −0.29. There are 24 possible ways to decompose the total effect into one direct effect, one indirect effect through m1, one indirect effect through m2, and one indirect effect through m1 and m2. We do not explore each of these decompositions in this introduction. However, a review of these effects indicates that the largest proportion of the total effect can be attributed to the indirect effect through m1 alone.

Sometimes, the research question allows us to focus on a more coarse decomposition. For instance, if we wanted to focus on the effect through m1 alone and on any effect that involves m2, we could estimate mediator-specific natural effects which isolate the effect through m1 and combine the effects through m2 alone with those through both m1 and m2. This decomposition of effects is known as type-1 mediator-specific effects, and we specify the mseffects(m1) option in mediate to estimate them.

```
. mediate (y) (m2) (m1) (t), sequential tinteraction minteraction
> meqtinteraction mseffects(m1)
Iteration 0:  EE criterion = 6.373e-21
Iteration 1:  EE criterion = 2.787e-28
Causal mediation analysis                              Number of obs = 2,000
Mediation type: Sequential
Mediator 1:     m1
Mediator 2:     m2
Treatment type: Binary
MS effects:     Type 1
```

y	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
MS-NDE						
00	-2.137034	.1755708	-12.17	0.000	-2.481146	-1.792921
01	-2.210278	.284549	-7.77	0.000	-2.767984	-1.652573
10	-1.841115	.2914441	-6.32	0.000	-2.412335	-1.269895
11	-2.044882	.1971614	-10.37	0.000	-2.431311	-1.658453
MS-NIE1						
00	-3.277243	.3619214	-9.06	0.000	-3.986596	-2.56789
01	-3.389729	.3789566	-8.94	0.000	-4.132471	-2.646988
10	-2.981325	.3508021	-8.50	0.000	-3.668884	-2.293765
11	-3.224333	.4005567	-8.05	0.000	-4.00941	-2.439256
MS-NIE2						
00	-.1873689	.1647989	-1.14	0.256	-.5103689	.1356311
01	-.299855	.1591053	-1.88	0.059	-.6116956	.0119857
10	-.2606136	.218082	-1.20	0.232	-.6880465	.1668193
11	-.5036221	.2198351	-2.29	0.022	-.934491	-.0727532
TE						
t						
(Yes vs No)	-5.62198	.452873	-12.41	0.000	-6.509595	-4.734365

```
Note: Outcome equation includes treatment-mediator interactions and
      mediator-mediator interaction, and mediator 2 equation includes
      treatment-mediator interaction.
```

We now obtain only four estimates each of mediator-specific direct effects, indirect effects through `m1` alone, and indirect effects involving `m2`. The estimates in the section labeled `MS-NIE1` are the mediator-specific natural indirect effects through `m1`. The estimates in the section labeled `MS-NIE2` are the mediator-specific natural indirect effects through both pathways involving `m2`

It is similarly possible to estimate mediator-specific effects that isolate the pathway through `m2` alone, which are known as type-2 mediator-specific effects, by specifying the `mseffects(m2)` option.

As in the one-mediator case, causal inference based on estimates like those shown here requires making assumptions of no unobserved confounding. The assumptions are natural extensions of those required with one mediator.

Above, we have previewed of the effects that can be estimated in the two-mediator case and shown how those effects grow quickly in number as we increase the number of mediators. This complexity is reduced as we allow for less flexibility by omitting interactions in our models or when the mediators are parallel rather than sequential. For more conceptual and technical details, command syntax, and worked examples using `mediate` with two mediators, see [CAUSAL] **mediate multiple** and the references provided there.

References

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Nguyen, T. Q., I. Schmid, and E. A. Stuart. 2021. Clarifying causal mediation analysis for the applied researcher: Defining effects based on what we want to learn. *Psychological Methods* 26: 255–271. https://doi.org/10.1037/met0000299.

Also see

[CAUSAL] **mediate** — Causal mediation analysis (one mediator)

[CAUSAL] **mediate multiple** — Causal mediation analysis (two mediators)+