Lecture 10: Conditional Process Analysis

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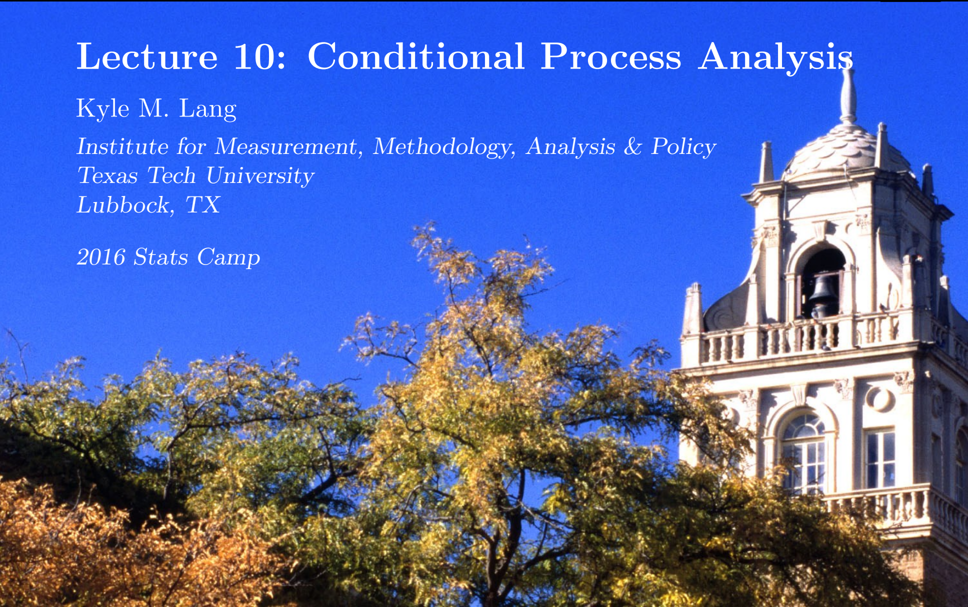


Outline

- Conceptual introduction to conditional process analysis
- Define conditional direct and indirect effects
- Examples of some basic conditional process models
- Run through some basic examples of conditional process models

Starting Point

So far, we've been discussing mediation and moderation as independent hypotheses.

- With mediation, we're interested in describing the chain of events by which X influences Y.
  - We want to model the process by which X affects Y.
  - We're asking questions about *how* X impacts Y.
- With moderation, we're interested in discovering how the relation between X and Y changes as a function of some moderating variable (or set of moderating variables).
  - We want to know at what levels of the moderator is the $X \rightarrow Y$ relation statistically significant.
  - We're asking questions about *when* X affects Y.

Conditional Process Analysis

We can combine the *how*-type questions answer by mediation models and the *when*-type questions answered by moderation analysis via *conditional process analysis*.

- With conditional process analysis, we're interested in assessing how an indirect effect (i.e., a process) changes as a function of some set of moderating variables (i.e., is conditional on those moderators).
- We want to estimate *conditional indirect (direct) effects*.
- This type of model is often called *moderated mediation*.

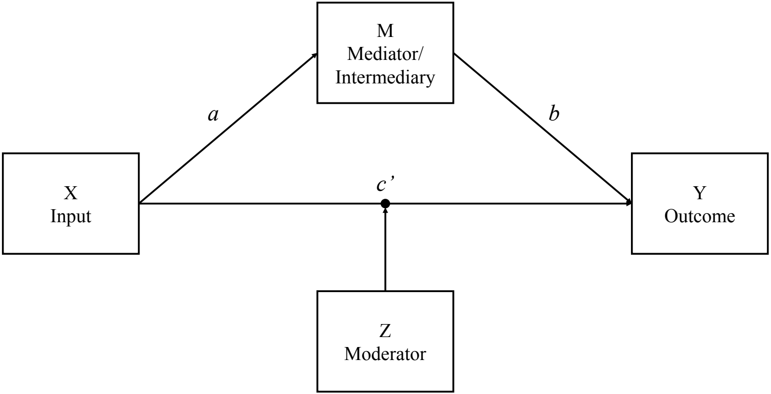
Conditional Process Analysis

We can also ask questions about how the effect of an interaction term is transmitted through a mediator to the focal outcome.

- This type of model is called *mediated moderation*.
- It turns out that mediated moderation is mathematically equivalent to moderated mediation.
- Mediated moderation is, nearly always, impossible to interpret (more on that later).

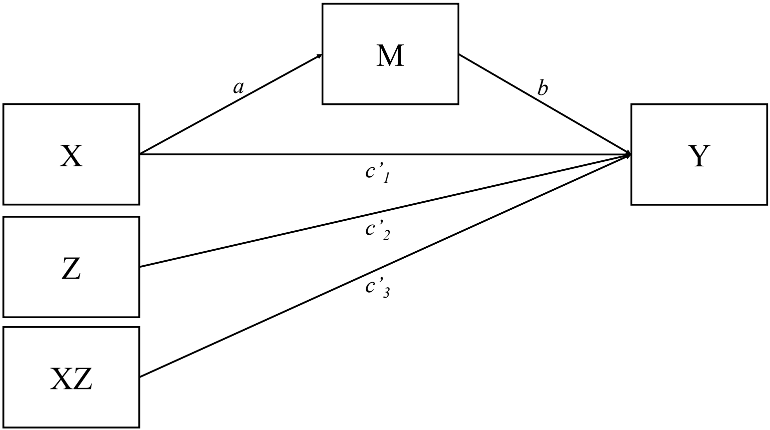
Simplest Example

The simplest example of a conditional process model includes only the direct effect as conditional:



Simplest Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Simplest Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'_1X + c'_2Z + c'_3XZ + e_Y \tag{1}$$

$$M = i_2 + aX + e_M \tag{2}$$

Simplest Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'_1 X + c'_2 Z + c'_3 XZ + e_Y \tag{1}$$

$$M = i_2 + aX + e_M \tag{2}$$

In this simple case, the indirect effect is not conditional, so it is defined as before:

$$IE = ab$$

Simplest Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c_1'X + c_2'Z + c_3'XZ + e_Y \quad (1)$$

$$M = i_2 + aX + e_M \quad (2)$$

In this simple case, the indirect effect is not conditional, so it is defined as before:

$$IE = ab$$

The direct effect, on the other hand, must be interpreted as conditional on Z.

Simplest Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'_1X + c'_2Z + c'_3XZ + e_Y \tag{1}$$

$$M = i_2 + aX + e_M \tag{2}$$

In this simple case, the indirect effect is not conditional, so it is defined as before:

$$IE = ab$$

The direct effect, on the other hand, must be interpreted as conditional on Z.

We can rearrange Equation 1 to get:

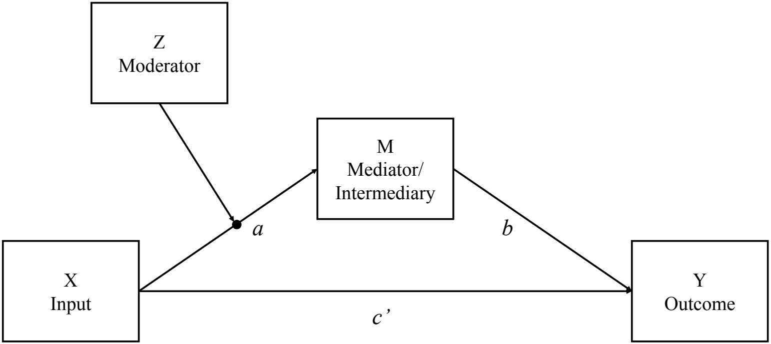
$$Y = i_1 + bM + c'_2Z + \left(c'_1 + c'_3Z\right)X + e_Y$$

The conditional direct effect is the simple slope linking X to Y:

$$DE = c'_1 + c'_3Z$$

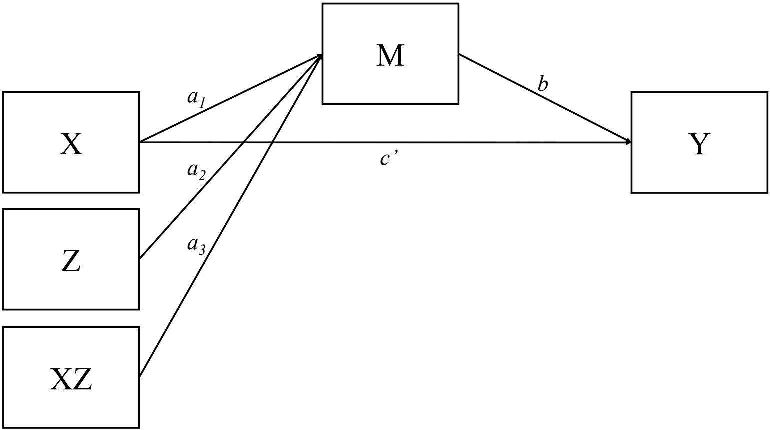
Another Example

A somewhat more interesting example of a conditional process model includes a conditional indirect effect induced by moderation of the *a* path:



Another Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'X + e_Y \tag{3}$$

$$M = i_2 + a_1X + a_2Z + a_3XZ + e_M \tag{4}$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'X + e_Y \tag{3}$$

$$M = i_2 + a_1X + a_2Z + a_3XZ + e_M \tag{4}$$

In this case, the direct effect is now unconditional, so it is defined as in simple mediation analysis:

$$DE = c'$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'X + e_Y \tag{3}$$

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In this case, the direct effect is now unconditional, so it is defined as in simple mediation analysis:

$$DE = c'$$

Now, the indirect effect must be interpreted as conditional on Z due to the a path being moderated by Z.

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'X + e_Y \tag{3}$$

$$M = i_2 + a_1X + a_2Z + a_3XZ + e_M \tag{4}$$

In this case, the direct effect is now unconditional, so it is defined as in simple mediation analysis:

$$DE = c'$$

Now, the indirect effect must be interpreted as conditional on Z due to the a path being moderated by Z.

We can rearrange Equation 4 to get:

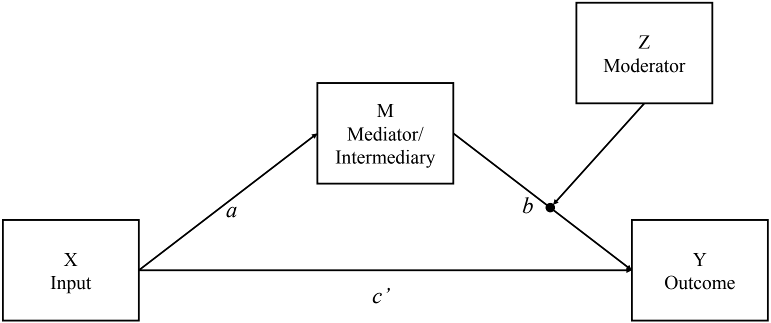
$$M = i_2 + a_2Z + (a_1 + a_3Z)\,X + e_M$$

The conditional indirect effect is now defined by the following product:

$$IE = (a_1 + a_3Z)\,b$$

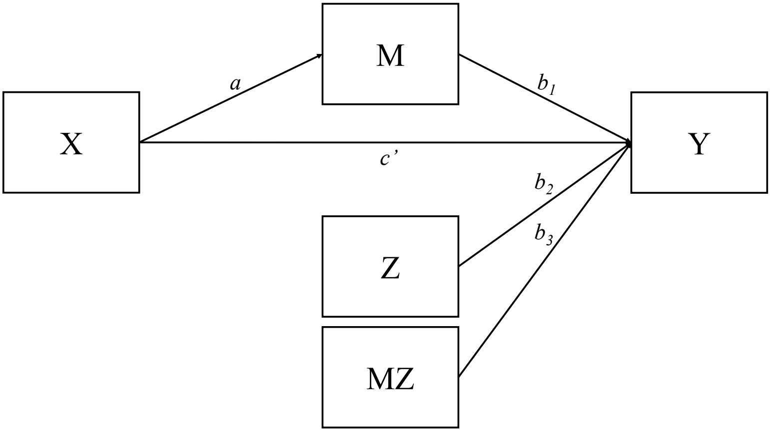
Another Example

The conditional indirect effect can also be induced by moderation of the b path:



Another Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1 M + b_2 Z + b_3 MZ + e_Y \tag{5}$$

$$M = i_2 + aX + e_M \tag{6}$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1 M + b_2 Z + b_3 MZ + e_Y \tag{5}$$

$$M = i_2 + aX + e_M \tag{6}$$

As above, the direct effect is unconditional:

$$DE = c'$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1 M + b_2 Z + b_3 MZ + e_Y \tag{5}$$

$$M = i_2 + aX + e_M \tag{6}$$

As above, the direct effect is unconditional:

$$DE = c'$$

Again, the indirect effect is conditional on Z due to the b path being moderated by Z.

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1 M + b_2 Z + b_3 MZ + e_Y \tag{5}$$

$$M = i_2 + aX + e_M \tag{6}$$

As above, the direct effect is unconditional:

$$DE = c'$$

Again, the indirect effect is conditional on Z due to the b path being moderated by Z.

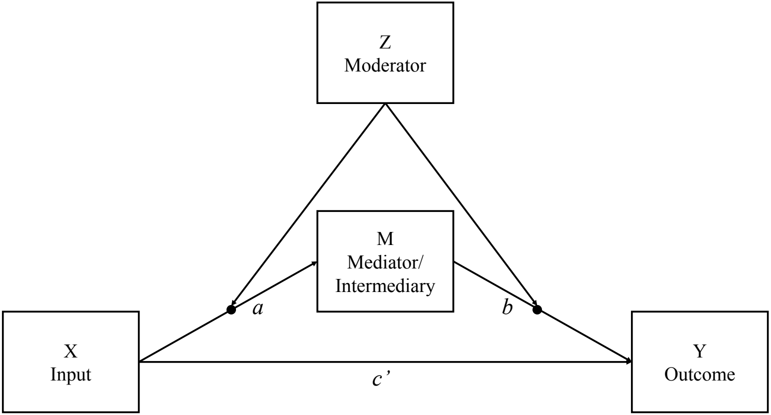
We can rearrange Equation 5 to get:

$$Y = i_1 + b_2 Z + (b_1 + b_3 Z)\, M + e_Y$$

So, the conditional indirect effect is defined by the following product:

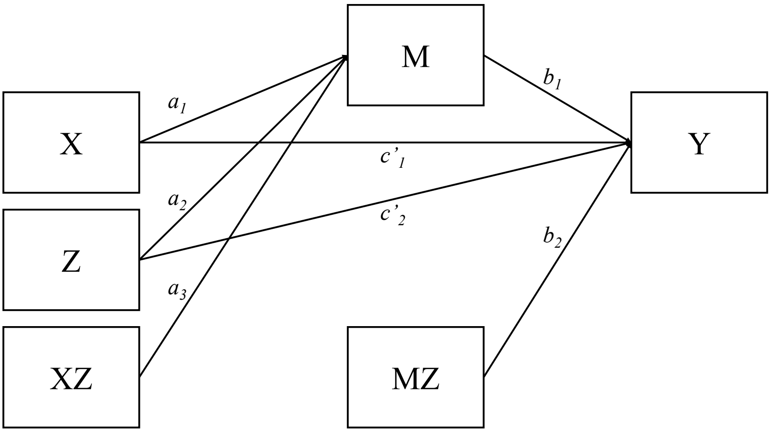
$$IE = a\,(b_1 + b_3 Z)$$

Maybe, we have a conditional indirect effect because Z moderates both the a and b paths:



Another Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c_1' X + c_2' Z + b_1 M + b_2 MZ + e_Y \tag{7}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{8}$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c_1' X + c_2' Z + b_1 M + b_2 MZ + e_Y \tag{7}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{8}$$

The direct effect is still unconditional:

$$DE = c_1'$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c_1' X + c_2' Z + b_1 M + b_2 MZ + e_Y \tag{7}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{8}$$

The direct effect is still unconditional:

$$DE = c_1'$$

The indirect effect is conditional on Z due to the a and b paths being moderated by Z.

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c_1' X + c_2' Z + b_1 M + b_2 MZ + e_Y \quad (7)$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \quad (8)$$

The direct effect is still unconditional:

$$DE = c_1'$$

The indirect effect is conditional on Z due to the a and b paths being moderated by Z.

We can rearrange Equations 7 and 8 to get:

$$Y = i_1 + c_2' Z + (b_1 + b_2 Z) M + e_Y$$

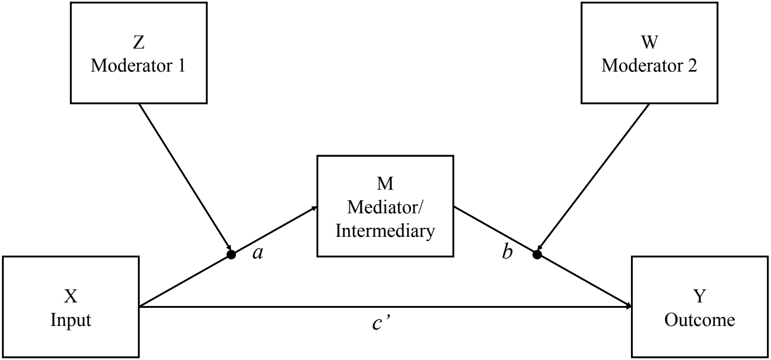
$$M = i_2 + a_2 Z + (a_1 + a_3 Z) X + e_M$$

So, the conditional indirect effect is defined by the following product:

$$IE = (a_1 + a_3 Z)(b_1 + b_2 Z)$$

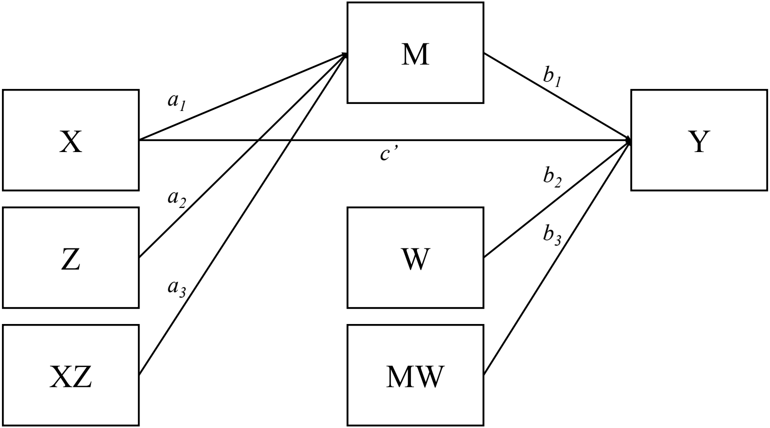
Another Example

A conditional indirect effect can arise when the a and b paths are moderated by separate variables:



Another Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1 M + b_2 W + b_3 MW + e_Y \tag{9}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{10}$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1 M + b_2 W + b_3 MW + e_Y \tag{9}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{10}$$

The direct effect is still unconditional:

$$DE = c'$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1M + b_2W + b_3MW + e_Y \tag{9}$$

$$M = i_2 + a_1X + a_2Z + a_3XZ + e_M \tag{10}$$

The direct effect is still unconditional:

$$DE = c'$$

The indirect effect is now conditional on both Z and W since these variables moderate the a and b paths, respectively.

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + c'X + b_1 M + b_2 W + b_3 MW + e_Y \tag{9}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{10}$$

The direct effect is still unconditional:

$$DE = c'$$

The indirect effect is now conditional on both Z and W since these variables moderate the a and b paths, respectively.

We can rearrange Equations 9 and 10 to get:

$$Y = i_1 + b_2 W + (b_1 + b_3 W) M + e_Y$$

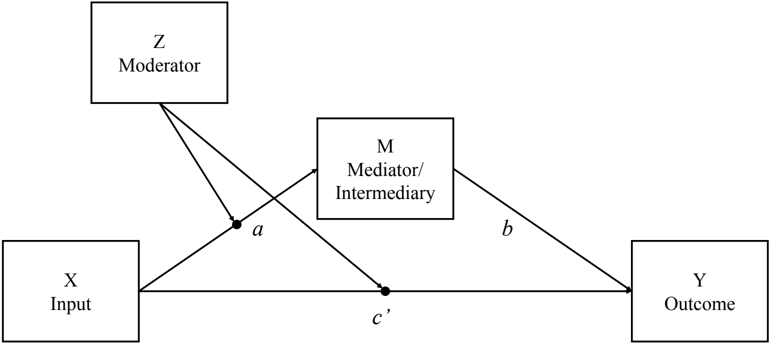
$$M = i_2 + a_2 Z + (a_1 + a_3 Z) X + e_M$$

So, the conditional indirect effect is defined by the following product:

$$IE = (a_1 + a_3 Z)(b_1 + b_3 W)$$

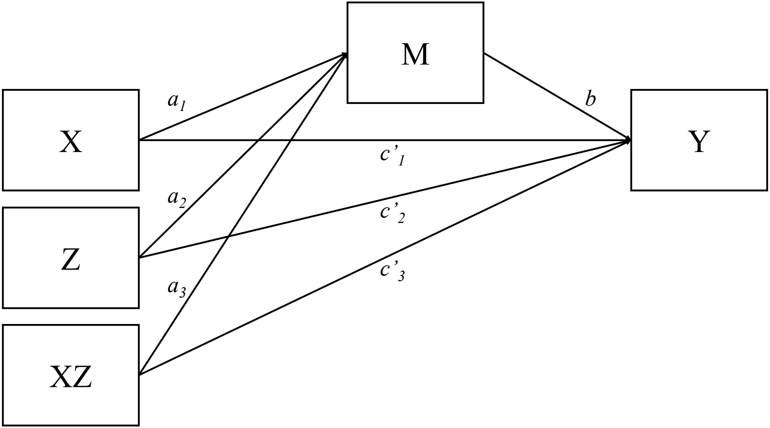
Another Example

We could have conditional indirect and direct effects due to moderation by a single variable:



Another Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c'_1 X + c'_2 Z + c'_3 XZ + e_Y \tag{11}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{12}$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c_1'X + c_2'Z + c_3'XZ + e_Y \tag{11}$$

$$M = i_2 + a_1X + a_2Z + a_3XZ + e_M \tag{12}$$

Both the direct and indirect effects are now conditional on Z since it moderates the a and c' paths.

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + bM + c_1'X + c_2'Z + c_3'XZ + e_Y \tag{11}$$

$$M = i_2 + a_1X + a_2Z + a_3XZ + e_M \tag{12}$$

Both the direct and indirect effects are now conditional on Z since it moderates the a and c' paths.

We can rearrange Equations 11 and 12 to get:

$$Y = i_1 + bM + c_2'Z + \left(c_1' + c_3'Z\right)X + e_Y$$

$$M = i_2 + a_2Z + (a_1 + a_3Z)\,X + e_M$$

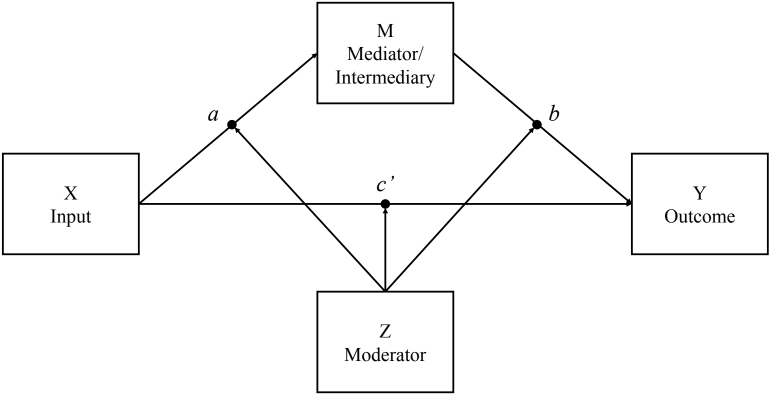
So, the conditional direct and indirect effects are defined by the following:

$$DE = c_1' + c_3'Z$$

$$IE = (a_1 + a_3Z)\,b$$

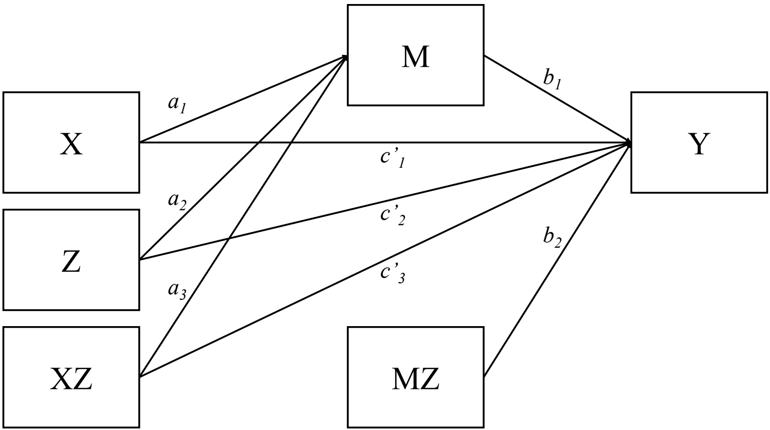
Another Example

We could have one moderator of the a, b, and c' paths inducing conditional indirect and direct effects:



Another Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + b_1 M + c'_1 X + c'_2 Z + b_2 MZ + c'_3 XZ + e_Y \tag{13}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{14}$$

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + b_1 M + c'_1 X + c'_2 Z + b_2 MZ + c'_3 XZ + e_Y \tag{13}$$
$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{14}$$

Both the direct and indirect effects are again conditional on Z since it moderates the a, b, and c' paths.

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + b_1 M + c'_1 X + c'_2 Z + b_2 MZ + c'_3 XZ + e_Y \tag{13}$$

$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M \tag{14}$$

Both the direct and indirect effects are again conditional on Z since it moderates the a, b, and c' paths.

We can rearrange Equations 13 and 14 to get:

$$Y = i_1 + c'_2 Z + (b_1 + b_2 Z)\, M + \left(c'_1 + c'_3 Z\right) X + e_Y$$

$$M = i_2 + a_2 Z + (a_1 + a_3 Z)\, X + e_M$$

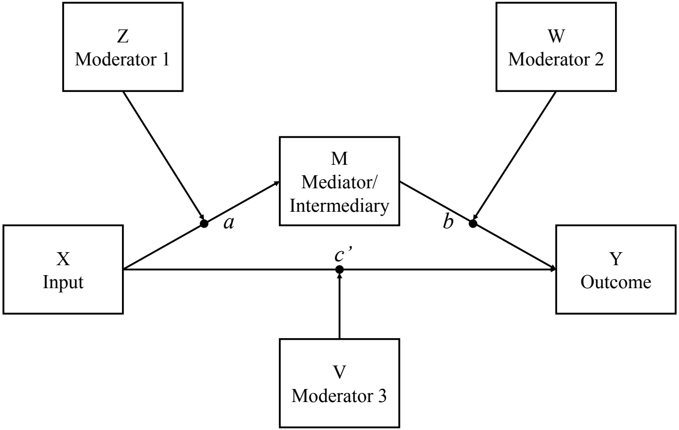
So, the conditional direct and indirect effects are defined by the following:

$$DE = c'_1 + c'_3 Z$$

$$IE = (a_1 + a_3 Z)\,(b_1 + b_2 Z)$$

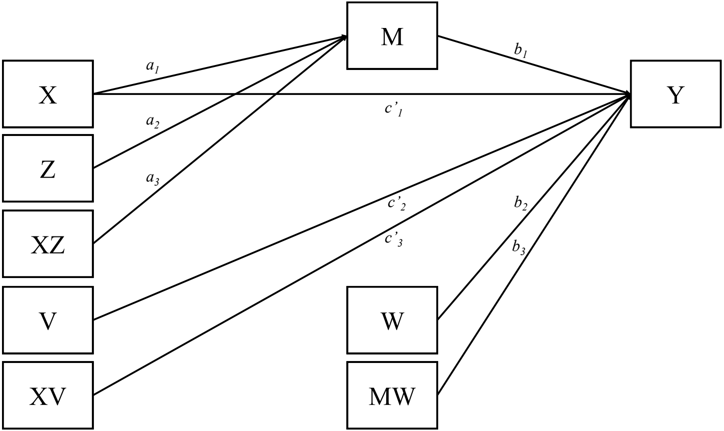
Another Example

Or maybe, the a, b, and c' paths are each moderated by a separate variable to induce the conditional indirect and direct effects:



Another Example

The preceding conceptual diagram corresponds to the following analytic diagram:



Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + b_1 M + b_2 W + c_1' X + c_2' V + c_3' XV + b_3 MW + e_Y$$
$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M$$

Another Example

This analytic diagram implies the following equations:

$$
\begin{aligned}
Y &= i_1 + b_1 M + b_2 W + c_1' X + c_2' V + c_3' XV + b_3 MW + e_Y \\
M &= i_2 + a_1 X + a_2 Z + a_3 XZ + e_M
\end{aligned}
$$

The direct effect is now conditional on V, while the indirect effect is conditional on Z and W.

Another Example

This analytic diagram implies the following equations:

$$Y = i_1 + b_1 M + b_2 W + c_1' X + c_2' V + c_3' XV + b_3 MW + e_Y$$
$$M = i_2 + a_1 X + a_2 Z + a_3 XZ + e_M$$

The direct effect is now conditional on V, while the indirect effect is conditional on Z and W.

We can rearrange the preceding equations to get:

$$Y = i_1 + b_2 W + c_2' V + (b_1 + b_2 W) M + \left(c_1' + c_3' V\right) X + e_Y$$
$$M = i_2 + a_2 Z + (a_1 + a_3 Z) X + e_M$$

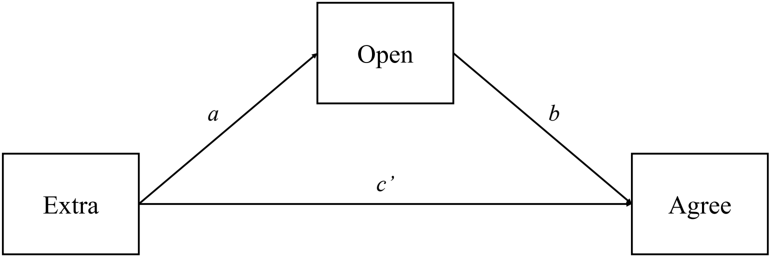
So, the conditional direct and indirect effects are defined by the following:

$$DE = c_1' + c_3' V$$
$$IE = (a_1 + a_3 Z)(b_1 + b_3 W)$$

Example

Okay, let's do an example analysis.

We'll start by fitting the following simple indirect effects model to the `bfi` data from the **psych** package:



Example

```
library(lavaan)
dat1 <- readRDS("../data/lecture10Data.rds")
nBoot <- 5000
## Simple indirect effects model:
mod1 <- "
agree ~ b*open + cp*extra
open ~ a*extra

ab := a*b
"
out1 <- sem(mod1, data = dat1, se = "boot", boot = nBoot)
summary(out1)
```

```
lavaan (0.5-20) converged normally after  16 iterations

  Number of observations                          2800

  Estimator                                         ML
  Minimum Function Test Statistic                0.000
  Degrees of freedom                                 0
  Minimum Function Value               0.0000000000000
```

Example

```
Parameter Estimates:

  Information                                      Observed
  Standard Errors                                 Bootstrap
  Number of requested bootstrap draws                  5000
  Number of successful bootstrap draws                 4990

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)
  agree ~
    open      (b)     0.166    0.028    6.047    0.000
    extra    (cp)     0.358    0.027   13.473    0.000
  open ~
    extra     (a)     0.268    0.023   11.601    0.000

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)
    agree             0.487    0.015   33.156    0.000
    open              0.294    0.010   30.283    0.000

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)
    ab                0.045    0.009    5.015    0.000
```

Example

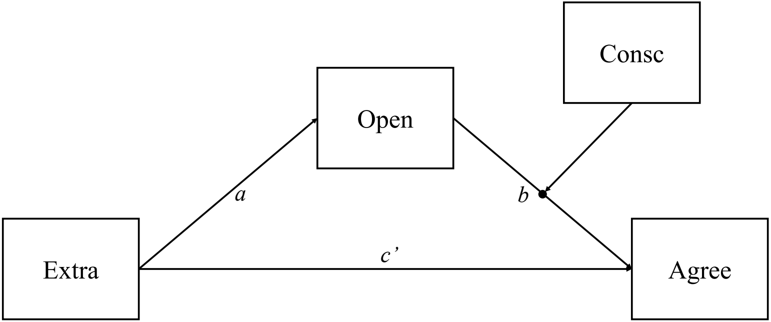
```
tab1 <-
    parameterEstimates(out1, boot.ci.type = "bca.simple")
tab1[grep("ab", tab1$label),
     c("label", "est", "ci.lower", "ci.upper")]
```

```
  label    est ci.lower ci.upper
7    ab  0.045    0.029    0.063
```

Example

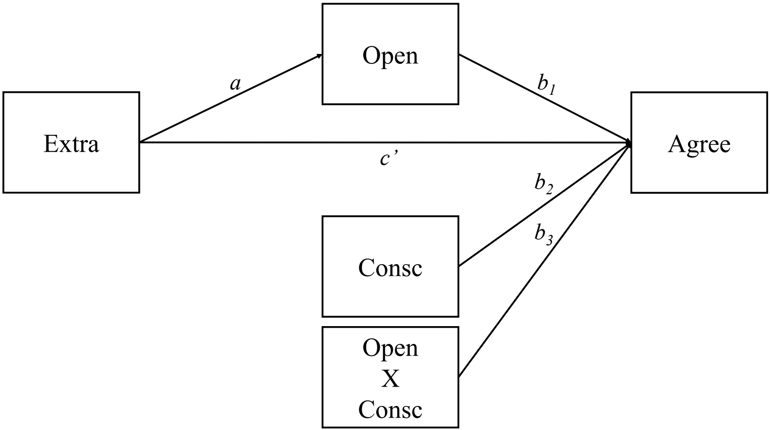
Maybe we suspect that *conscientiousness* moderates the effect of *openness* on *agreeableness* (i.e., the b path).

We can assess this conditional process via the following model:



Example

The preceding conceptual model translates into the following analytic model:



Example

```r
## Construct the product term:
dat1$openXconsc <- dat1$open*dat1$consc
## Find interesting quantiles of 'consc':
quantile(dat1$consc, c(0.25, 0.50, 0.75))
```

```
    25%     50%     75%
-0.4045 -0.0045  0.3955
```

```r
## Conditional process model with b path moderated:
mod2 <- "
agree ~ b1*open + cp*extra + b2*consc + b3*openXconsc
open ~ a*extra

abLo  := a*(b1 + b3*(-0.4045))
abMid := a*(b1 + b3*(-0.0045))
abHi  := a*(b1 + b3*0.3955)
"
```

Example

```
out2 ← sem(mod2, data = dat1, se = "boot", boot = nBoot)
summary(out2)
```

```
lavaan (0.5-20) converged normally after  17 iterations

  Number of observations                          2800

  Estimator                                         ML
  Minimum Function Test Statistic              161.865
  Degrees of freedom                                 2
  P-value (Chi-square)                           0.000

Parameter Estimates:

  Information                                 Observed
  Standard Errors                            Bootstrap
  Number of requested bootstrap draws             5000
  Number of successful bootstrap draws            5000

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)
  agree ~
```

Example

```
    open       (b1)    0.167    0.027    6.116    0.000
    extra      (cp)    0.361    0.026   14.014    0.000
    consc      (b2)   -0.028    0.026   -1.057    0.290
    openXcnsc  (b3)   -0.079    0.039   -2.045    0.041
  open ~
    extra       (a)    0.268    0.023   11.506    0.000

Variances:
                    Estimate  Std.Err  Z-value  P(>|z|)
    agree              0.485    0.015   32.930    0.000
    open               0.294    0.010   30.497    0.000

Defined Parameters:
                    Estimate  Std.Err  Z-value  P(>|z|)
    abLo               0.053    0.010    5.101    0.000
    abMid              0.045    0.009    5.224    0.000
    abHi               0.036    0.009    4.180    0.000
```

Example

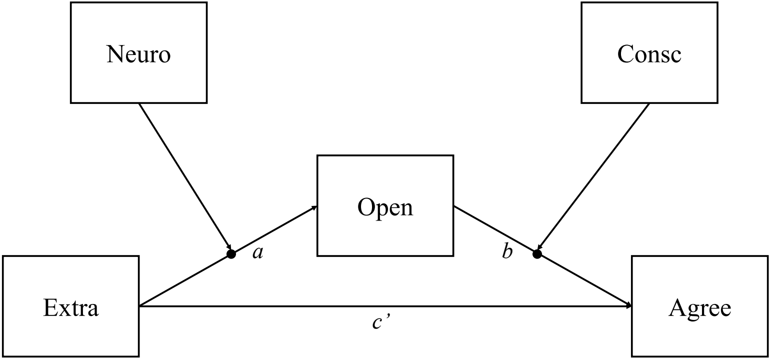
```r
tab2 ←
    parameterEstimates(out2, boot.ci.type = "bca.simple")
tab2[grep("ab", tab2$label),
     c("label", "est", "ci.lower", "ci.upper")]
```

```
   label   est ci.lower ci.upper
14  abLo 0.053    0.034    0.076
15 abMid 0.045    0.029    0.064
16  abHi 0.036    0.021    0.055
```

Example

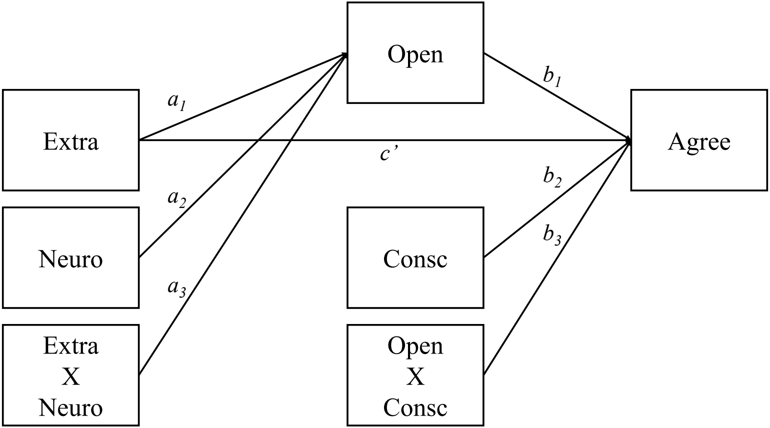
Suppose we also think that *neuroticism* moderates the effect of *extroversion* on *openness* (i.e., the a path).

We can assess this conditional process via the following model:



Example

The preceding conceptual model translates into the following analytic model:



Example

```r
## Construct another product term:
dat1$extraXneuro <- dat1$extra*dat1$neuro
## Find interesting quantiles of 'neuro':
quantile(dat1$neuro, c(0.25, 0.50, 0.75))
```

```
       25%        50%        75%
-0.9622679 -0.1622679  0.8377321
```

```r
## Conditional process model with a and b paths moderated:
mod3 <- "
agree ~ b1*open + cp*extra + b2*consc + b3*openXconsc
open ~ a1*extra + a2*neuro + a3*extraXneuro

abLoLo   := (a1 + a3*(-0.962268)) * (b1 + b3*(-0.4045))
abLoMid  := (a1 + a3*(-0.962268)) * (b1 + b3*(-0.0045))
abLoHi   := (a1 + a3*(-0.962268)) * (b1 + b3*0.3955)

abMidLo   := (a1 + a3*(-0.162268)) * (b1 + b3*(-0.4045))
abMidMid  := (a1 + a3*(-0.162268)) * (b1 + b3*(-0.0045))
abMidHi   := (a1 + a3*(-0.162268)) * (b1 + b3*0.3955)

abHiLo   := (a1 + a3*0.837732) * (b1 + b3*(-0.4045))
abHiMid  := (a1 + a3*0.837732) * (b1 + b3*(-0.0045))
abHiHi   := (a1 + a3*0.837732) * (b1 + b3*0.3955)
"
```

Example

```
out3 ← sem(mod3, data = dat1, se = "boot", boot = nBoot)
summary(out3)
```

```
lavaan (0.5-20) converged normally after  18 iterations

  Number of observations                          2800

  Estimator                                         ML
  Minimum Function Test Statistic              214.855
  Degrees of freedom                                 4
  P-value (Chi-square)                           0.000

Parameter Estimates:

  Information                                 Observed
  Standard Errors                            Bootstrap
  Number of requested bootstrap draws             5000
  Number of successful bootstrap draws            5000

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)
  agree ~
```

Example

```
    open        (b1)    0.167    0.027    6.074    0.000
    extra       (cp)    0.361    0.027   13.549    0.000
    consc       (b2)   -0.028    0.026   -1.057    0.290
    openXcnsc   (b3)   -0.079    0.039   -2.040    0.041
  open ~
    extra       (a1)    0.261    0.023   11.359    0.000
    neuro       (a2)    0.072    0.009    7.866    0.000
    extraXner   (a3)    0.005    0.022    0.214    0.830

Variances:
                     Estimate  Std.Err  Z-value  P(>|z|)
    agree               0.485    0.014   33.643    0.000
    open                0.287    0.009   30.369    0.000

Defined Parameters:
                     Estimate  Std.Err  Z-value  P(>|z|)
    abLoLo              0.051    0.012    4.219    0.000
    abLoMid             0.043    0.009    4.544    0.000
    abLoHi              0.035    0.009    4.066    0.000
    abMidLo             0.052    0.010    4.994    0.000
    abMidMid            0.043    0.008    5.177    0.000
    abMidHi             0.035    0.008    4.199    0.000
    abHiLo              0.053    0.010    5.449    0.000
```

Example

abHiMid	0.044	0.009	5.200	0.000
abHiHi	0.036	0.009	3.901	0.000

Example

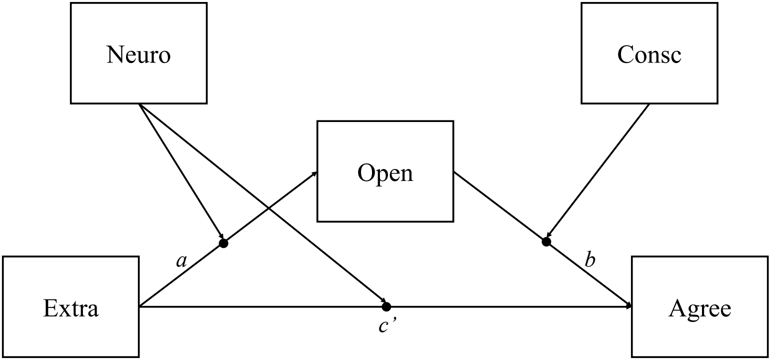
```
tab3 ←
    parameterEstimates(out3, boot.ci.type = "bca.simple")
tab3[grep("ab", tab3$label),
     c("label", "est", "ci.lower", "ci.upper")]
```

```
      label   est ci.lower ci.upper
25   abLoLo 0.051    0.030    0.078
26  abLoMid 0.043    0.026    0.064
27   abLoHi 0.035    0.019    0.053
28  abMidLo 0.052    0.033    0.074
29 abMidMid 0.043    0.028    0.062
30  abMidHi 0.035    0.019    0.052
31   abHiLo 0.053    0.035    0.072
32  abHiMid 0.044    0.029    0.062
33   abHiHi 0.036    0.019    0.055
```

Example

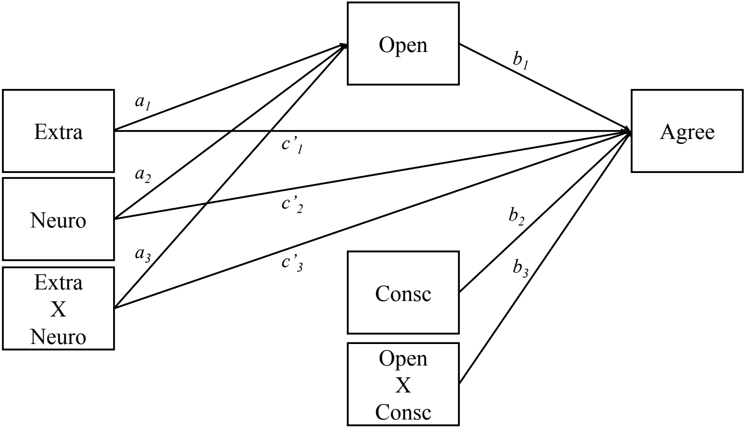
Finally, maybe we think that *neuroticism* also moderates the direct effect of *extroversion* on *agreeableness* (i.e., the c' path).

We can assess this conditional process via the following model:



Example

The preceding conceptual model translates into the following analytic model:



Example

```
## Conditional process model with a, b, c paths moderated:
mod4 <- "
agree ~ b1*open + b2*consc + cp1*extra + cp2*neuro +
        cp3*extraXneuro + b3*openXconsc
open ~ a1*extra + a2*neuro + a3*extraXneuro

cpLo  := cp1 + cp3*(-0.962268)
cpMid := cp1 + cp3*(-0.162268)
cpHi  := cp1 + cp3*0.837732

abLoLo  := (a1 + a3*(-0.962268)) * (b1 + b3*(-0.4045))
abLoMid := (a1 + a3*(-0.962268)) * (b1 + b3*(-0.0045))
abLoHi  := (a1 + a3*(-0.962268)) * (b1 + b3*0.3955)

abMidLo  := (a1 + a3*(-0.162268)) * (b1 + b3*(-0.4045))
abMidMid := (a1 + a3*(-0.162268)) * (b1 + b3*(-0.0045))
abMidHi  := (a1 + a3*(-0.162268)) * (b1 + b3*0.3955)

abHiLo  := (a1 + a3*0.837732) * (b1 + b3*(-0.4045))
abHiMid := (a1 + a3*0.837732) * (b1 + b3*(-0.0045))
abHiHi  := (a1 + a3*0.837732) * (b1 + b3*0.3955)
"
```

Example

```r
out4 <- sem(mod4, data = dat1, se = "boot", boot = nBoot)
summary(out4)
```

```
lavaan (0.5-20) converged normally after  20 iterations

  Number of observations                          2800

  Estimator                                         ML
  Minimum Function Test Statistic              128.914
  Degrees of freedom                                 2
  P-value (Chi-square)                           0.000

Parameter Estimates:

  Information                                 Observed
  Standard Errors                            Bootstrap
  Number of requested bootstrap draws             5000
  Number of successful bootstrap draws            5000

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)
  agree ~
```

Example

```
    open       (b1)    0.191    0.027    6.978    0.000
    consc      (b2)    0.021    0.027    0.772    0.440
    extra     (cp1)    0.349    0.027   13.047    0.000
    neuro     (cp2)   -0.102    0.012   -8.516    0.000
    extraXnr  (cp3)    0.049    0.022    2.219    0.026
    opnXcnsc   (b3)   -0.074    0.045   -1.654    0.098
  open ~
    extra      (a1)    0.261    0.023   11.206    0.000
    neuro      (a2)    0.072    0.009    7.972    0.000
    extraXnr   (a3)    0.005    0.022    0.215    0.830

Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)
    agree             0.471    0.014   32.854    0.000
    open              0.287    0.010   29.976    0.000

Defined Parameters:
                   Estimate  Std.Err  Z-value  P(>|z|)
    cpLo              0.302    0.036    8.403    0.000
    cpMid             0.341    0.027   12.458    0.000
    cpHi              0.390    0.031   12.664    0.000
    abLoLo            0.057    0.013    4.228    0.000
    abLoMid           0.049    0.010    4.774    0.000
```

Example

abLoHi	0.041	0.009	4.558	0.000
abMidLo	0.057	0.011	5.105	0.000
abMidMid	0.050	0.009	5.646	0.000
abMidHi	0.042	0.009	4.833	0.000
abHiLo	0.058	0.010	5.795	0.000
abHiMid	0.051	0.009	5.863	0.000
abHiHi	0.043	0.010	4.482	0.000

Example

```
tab4 ←
    parameterEstimates(out4, boot.ci.type = "bca.simple")
tab4[grep("Lo|Mid|Hi", tab4$label),
     c("label", "est", "ci.lower", "ci.upper")]
```

```
       label   est ci.lower ci.upper
27      cpLo 0.302    0.234    0.375
28     cpMid 0.341    0.290    0.397
29      cpHi 0.390    0.330    0.451
30    abLoLo 0.057    0.034    0.087
31   abLoMid 0.049    0.032    0.073
32    abLoHi 0.041    0.025    0.062
33   abMidLo 0.057    0.038    0.082
34  abMidMid 0.050    0.034    0.069
35   abMidHi 0.042    0.026    0.060
36    abHiLo 0.058    0.040    0.080
37   abHiMid 0.051    0.035    0.069
38    abHiHi 0.043    0.026    0.063
```

Example

The a path was not significantly moderated in any of the previous models.

- Maybe we should try culling that path to see if we can get a more parsimonious description of the process.

```
## Conditional process model with b, c paths moderated:
mod5 <- "
agree ~ b1*open + b2*consc + cp1*extra + cp2*neuro +
        cp3*extraXneuro + b3*openXconsc
open ~ a*extra

cpLo  := cp1 + cp3*(-0.962268)
cpMid := cp1 + cp3*(-0.162268)
cpHi  := cp1 + cp3*0.837732

abLo := a * (b1 + b3*(-0.4045))
abMid := a * (b1 + b3*(-0.0045))
abHi := a * (b1 + b3*0.3955)
"
```

Example

```
out5 ← sem(mod5, data = dat1, se = "boot", boot = nBoot)
summary(out5)
```

```
lavaan (0.5-20) converged normally after  18 iterations

  Number of observations                          2800

  Estimator                                         ML
  Minimum Function Test Statistic              201.443
  Degrees of freedom                                 4
  P-value (Chi-square)                           0.000

Parameter Estimates:

  Information                                 Observed
  Standard Errors                            Bootstrap
  Number of requested bootstrap draws             5000
  Number of successful bootstrap draws            5000

Regressions:
                   Estimate  Std.Err  Z-value  P(>|z|)
  agree ~
```

Example

```
    open        (b1)     0.191     0.028     6.941     0.000
    consc       (b2)     0.021     0.027     0.774     0.439
    extra      (cp1)     0.349     0.027    13.030     0.000
    neuro      (cp2)    -0.102     0.012    -8.564     0.000
    extraXnr   (cp3)     0.049     0.022     2.210     0.027
    opnXcnsc    (b3)    -0.074     0.044    -1.671     0.095
  open ~
    extra        (a)     0.268     0.023    11.662     0.000

Variances:
                   Estimate   Std.Err   Z-value   P(>|z|)
    agree             0.471     0.014    32.521     0.000
    open              0.294     0.010    29.875     0.000

Defined Parameters:
                   Estimate   Std.Err   Z-value   P(>|z|)
    cpLo              0.302     0.036     8.459     0.000
    cpMid             0.341     0.027    12.473     0.000
    cpHi              0.390     0.031    12.502     0.000
    abLo              0.059     0.011     5.320     0.000
    abMid             0.051     0.009     5.778     0.000
    abHi              0.043     0.009     4.788     0.000
```

Example

```
tab5 ←
    parameterEstimates(out5, boot.ci.type = "bca.simple")
tab5[grep("Lo|Mid|Hi", tab5$label),
     c("label", "est", "ci.lower", "ci.upper")]
```

```
   label   est ci.lower ci.upper
25  cpLo 0.302    0.233    0.373
26 cpMid 0.341    0.289    0.394
27  cpHi 0.390    0.327    0.450
28  abLo 0.059    0.039    0.083
29 abMid 0.051    0.035    0.070
30  abHi 0.043    0.027    0.062
```