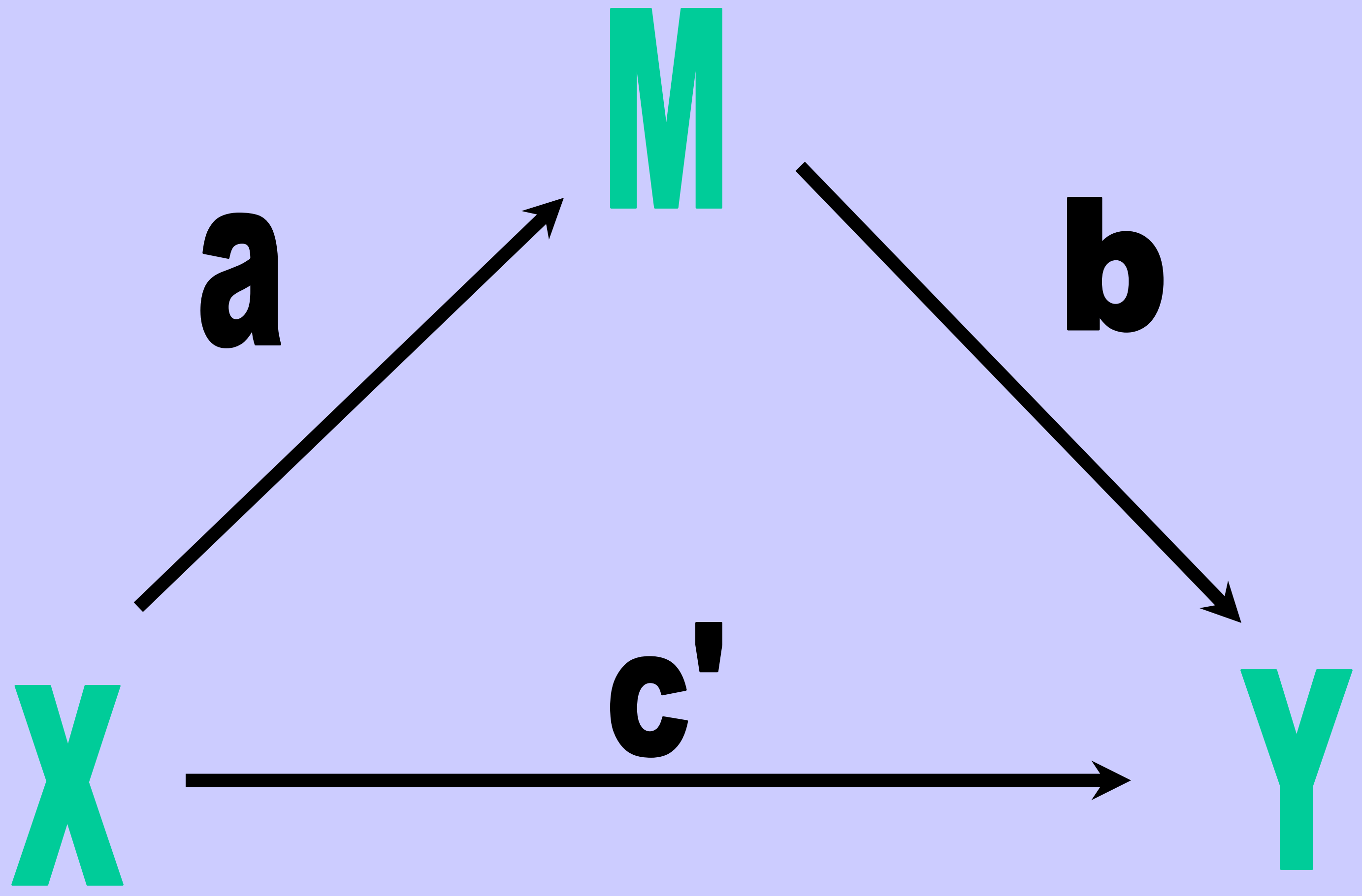
Estimating and Testing Mediation

The Beginning Model

$$X \xrightarrow{\quad c \quad} Y$$

The Mediational Model



The Four Paths

- **X → Y: path *c***
- **X → M: path *a***
- **M → Y (controlling for X): path *b***
- **X → Y (controlling for M): path *c′***

(standardized or unstandardized)

Baron and Kenny Steps

- **Step 1: X → Y (test path *c*)**
- **Step 2: X → M (test path *a*)**
- **Step 3: M (and X) → Y (test path *b*)**
- **Step 4: X (and M) → Y (test path *c'*)**

Note that Steps 3 and 4 use the same regression equation.

Total and Partial Mediation

- **Total Mediation**
  - **Meet steps 1, 2, and 3 and find that c' equal zero.**
- **Partial Mediation**
  - **Meet steps 1, 2, and 3 and find that c' is smaller in absolute value than c.**

Decomposition of Effects

Total Effect = Direct Effect + Indirect Effect

$$c = c' + ab$$

Note that

$$ab = c - c'$$

This equality exactly holds for multiple regression, but not necessarily for other estimation methods.

Percent of the total effect mediated:

ab/c **or** $1 - c'/c$

When Can We Conclude Complete Mediation?

When c′ is not statistically different from zero, but *c* is? NOT REALLY

The test of *c′* typically has much less power than the test of *ab*.

Ideally when *ab* is substantial and *c′* is small, we can conclude *complete mediation*.

Inconsistent Mediation

- ***ab*** **and *c′* have a different sign**
- **Example: Stress → Coping → Mood**
- **Like suppression in multiple regression.**
- **Consequences**
  - **Step 1 may fail**
  - **Percent mediated greater than 100%**
- **Do we have mediation?**
  - **Yes. There is an indirect effect (*ab* > 0).**
  - **No. There is no effect that is "mediated."**

Estimating the Total Effect (c)

The total effect or *c* can be inferred from direct and indirect effect as *c′* + *ab*.

We need not perform Step 1 to estimate *c*.

All Four Steps Essential?

- **Step 4 not required: partial mediation.**
- **Step 1 is important but not essential.**
  - **Power can be low if no direct effect even if there is mediation.**
  - **May fail to inconsistent mediation.**
- **Steps 2 and 3 are essential.**
- **Note that *ab* measures the indirect or the amount of the total effect that is mediated.**
- **Need a way of testing the null hypothesis that the indirect effect of *ab* is zero.**

Strategies to Test ab = 0

- **Joint significance of *a* and *b***
- **Sobel test**
- **Bootstrapping**
- **Monte Carlo**

Test a and b Separately

- **Easy to do**
- **Works fairly well**

Sobel Test of Mediation

Compute the square root of:

$$a^2 s_b{}^2 + b^2 s_a{}^2$$

which is denoted as s_{ab} .

Note that s_a and s_b are the standard errors of a and b, respectively; $t_a = a/s_a$ and $t_b = b/s_b$.

Divide ab by s_{ab} and treat that value as a Z.

So if ab/s_{ab} greater than 1.96 in absolute value, reject the null hypothesis that the indirect effect is zero.

Low power.

Bootstrapping

- **“Nonparametric” way of computing a sampling distribution.**
- **Re-sampling (with replacement)**
- **Many trials (computationally intensive)**
- **Compute a confidence interval which is asymmetric.**
- **Slight changes because empirically derived.**

How to Bootstrap

- SPSS Mixed ww has a bootstrap as an "add-on."
- MLwiN has a bootstrap option.
- Currently HLM and SAS do not.
- Preacher and Hayes have a macro for ordinary regression analysis.
- Many Structural Equation Modeling programs perform bootstrapping.
- Do not use "bias corrected" bootstrap.

Monte Carlo Method

- **Also called a *parametric bootstrap*.**
- **Input *a*, *b*, s_a, and s_b (and the correlation between a and b which is zero in this case).**
- **Assumes *a* and *b* have a normal distribution.**
- **Generates a distribution of *a* and *b* and so *ab* values.**
- **Use that for a CI and a *p* value**

Selig & Preacher Website

- **http://www.quantpsy.org/medmc/medmc.htm**
- **R function using the Selig & Preacher program**
  - **R program: mmc in dyadr**
  - **Gives *p* values as well as the CI**

Assumptions in Estimating Mediation

- **Standard General Linear Model Assumptions**
  - **Linearity**
  - **Normality of errors**
  - **Homogeneity of errors**
  - **Independence of errors**

1. Causal Assumptions in Estimating Mediation

- **M and X do not interact to cause Y.**
  - **If so, the b path changes as X changes.**
  - **X moderates the b path.**
- **Emphasized in earlier discussions of mediation but not mentioned by Baron & Kenny.**
- **Easily tested.**

2. Causal Assumptions in Estimating Mediation

- **No Reverse Causal Effects**
  - **M or Y not cause X**
  - **Y not cause M**
- **Aids**
  - **Randomization**
  - **Timing of Measurement**
  - **Theory**

3. Causal Assumptions in Estimating Mediation

- **No Omitted Variables (Confounders)**
  - **Between X and M**
  - **Between X and Y**
  - **Between M and Y**
- **Aids**
  - **Measuring them**
  - **Randomization**

4. Causal Assumptions in Estimating Mediation

- **No Measurement Error in X or M**
- **Aids**
  - **Enhance reliability**
  - **Correct for unreliability**
  - **Multiple indicators (latent variable SEM)**

Things May Not Be as Bad as It Might Seem

- **Manipulate X**
- **Primary worry then is measurement error in M and an omitted variable that causes M and Y.**
- **However, Fritz, Kenny, & MacKinnon show that these two biases may well offset each other!**