

## Multiple Mediator Model Example - - SAS, MPlus, and SPSS Handouts

This example is based on Harris and Rosenthal's (1985) four-mediator model for how teacher expectancies affect student achievement. Two mediators were examined in this study, social climate, a measure of verbal and nonverbal warmth, and input, the tendency to teach more material and more difficult material to high-expectancy students.

The data for the 40 subjects in this hypothetical study of teacher expectancies and student achievement are shown below where X is the teacher expectancy based on an intelligence test given to the student the previous year, M1 is the average observer rating of social warmth, M2 is the average observer rating of input to the student, and Y is the score on the test at the end of the semester.

Data for hypothetical study of teacher expectations and student achievement (Mackinnon, 2008, pp.113):

S#	X	M1	M2	Y	S#	X	M1	M2	Y
1	51	41	54	59	21	53	69	44	84
2	40	34	51	60	22	53	67	40	82
3	55	42	53	60	23	40	49	45	74
4	35	22	56	61	24	34	40	37	62
5	47	34	45	47	25	32	40	49	54
6	58	52	79	84	26	56	60	51	81
7	56	57	55	69	27	55	46	65	89
8	53	49	55	85	28	51	58	54	83
9	38	42	46	75	29	50	53	56	75
10	73	80	48	87	30	45	61	52	72
11	57	42	65	85	31	63	42	40	63
12	54	62	55	73	32	46	39	51	69
13	68	54	55	77	33	60	62	53	66
14	46	41	62	50	34	48	41	56	72
15	48	44	43	58	35	46	40	46	68
16	56	54	54	69	36	50	51	52	73
17	67	73	61	99	37	49	51	55	69
18	47	61	38	64	38	35	39	46	46
19	60	59	42	65	39	50	44	46	70
20	54	51	55	68	40	47	40	68	76

## SAS

### *Syntax*

\* The following program code reads in the dataset for the two mediator model example in MacKinnon 2008, Chapter 5. Five variables are defined: (a) subject ID#, (b) teacher expectancy, i.e., X, (c) social climate, i.e., M1, (d) input, i.e., M2, and (e) test score at the end of the semester, i.e., Y;

```
data a;
input s x m1 m2 y;
datalines;
  1    51    41    54    59
  2    40    34    51    60
.
.
. ;
```

\* The following commands run the four mediation regression equations outlined in Chapter 5 for two-mediator model example;

```
/* Equation 5.1 */
```

```
proc reg;
model y=x;
```

```
/* Equation 5.2. Note "covb" gives the covariance of the regression
coefficients. This value is needed for computing standard errors*/
```

```
model y=x m1 m2/covb;
```

```
/* Equation 5.3 */
```

```
model m1=x;
```

```
/* Equation 5.4 */
```

```
model m2=x;
run;
```

SAS Output:

**NOTE:**



There is one total effect and one direct effect, but two mediated effects in the model. This is why there are two  $b$  paths and two  $a$  paths, but only one  $c$  & one  $c'$ .

The REG Procedure  
Model: MODEL1  
Dependent Variable: y

Parameter Estimates

	Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t
$\hat{c}$ $\Rightarrow$	Intercept	1	34.72693	8.92472	3.89	0.0004
	x	1	0.70776	0.17343	4.08	0.0002

The REG Procedure  
Model: MODEL2  
Dependent Variable: y

Parameter Estimates

	Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t
$\hat{c}'$ $\Rightarrow$	Intercept	1	9.12333	10.47839	0.87	0.3897
	x	1	0.11215	0.20731	0.54	0.5919
	$\hat{b}_1$ $\Rightarrow$ m1	1	0.56903	0.15681	3.63	0.0009
	$\hat{b}_2$ $\Rightarrow$ m2	1	0.52972	0.16964	3.12	0.0035

Covariance of Estimates

Variable	Intercept	x	m1	m2
Intercept	109.79673207	-0.387895193	-0.495870555	-1.227545009
x	-0.387895193	0.0429780463	-0.022410629	-0.013017423
m1	-0.495870555	-0.022410629	0.02459002	0.0078936364
m2	-1.227545009	-0.013017423	0.0078936364	0.0287768709

$s_{\hat{b}_1 \hat{b}_2}$

The REG Procedure  
Model: MODEL3  
Dependent Variable: m1

**NOTE:** 

Although a single equation estimates both *b* paths (MODEL2), two models are needed to estimate the *a* paths (MODELS 3 and 4).

Parameter Estimates

	Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t
$\hat{a}_1 \Rightarrow$	Intercept	1	7.09702	8.12853	0.87	0.3881
	x	1	0.84014	0.15796	5.32	<.0001

The REG Procedure  
Model: MODEL4  
Dependent Variable: m2

Parameter Estimates

	Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t
$\hat{a}_2 \Rightarrow$	Intercept	1	40.71060	7.51397	5.42	<.0001
	x	1	0.22190	0.14602	1.52	0.1369

### Computation of Standard Errors for Specific & Total Mediated Effects

$$\begin{aligned}
 s_{\hat{a}_1\hat{b}_1} &= \sqrt{\hat{a}_1^2 s_{\hat{b}_1}^2 + \hat{b}_1^2 s_{\hat{a}_1}^2} \\
 &= \sqrt{(.84014^2)(.15681^2) + (.56903^2)(.15796^2)} \\
 &= .15948
 \end{aligned}$$

$$\begin{aligned}
 s_{\hat{a}_2\hat{b}_2} &= \sqrt{\hat{a}_2^2 s_{\hat{b}_2}^2 + \hat{b}_2^2 s_{\hat{a}_2}^2} \\
 &= \sqrt{(.22190^2)(.16964^2) + (.52972^2)(.14602^2)} \\
 &= .08602
 \end{aligned}$$

Equation 5.5

Standard errors for the two, *specific*, mediated effects.

$$\begin{aligned}
 s_{\hat{a}_1\hat{b}_1 + \hat{a}_2\hat{b}_2} &= \sqrt{s_{\hat{a}_1}^2 \hat{b}_1^2 + s_{\hat{b}_1}^2 \hat{a}_1^2 + s_{\hat{a}_2}^2 \hat{b}_2^2 + s_{\hat{b}_2}^2 \hat{a}_2^2 + 2\hat{a}_1\hat{a}_2 s_{\hat{b}_1\hat{b}_2}} \\
 &= \sqrt{(.15796^2)(.56903^2) + (.15681^2)(.84014^2) + (.14602^2)(.52972^2) +} \\
 &\quad \sqrt{(.16964^2)(.22190^2) + 2(.84014)(.22190)(.00789)} \\
 &= .18915
 \end{aligned}$$

Equation 5.7

Standard error for the *total* mediated effect.

### Testing Significance (i.e., computing z-scores) of Specific & Total Mediated Effects

$$\frac{\hat{a}_1\hat{b}_1}{s_{\hat{a}_1\hat{b}_1}} = \frac{.47806}{.15948} = 2.99765, p < .05$$

$$\frac{\hat{a}_2\hat{b}_2}{s_{\hat{a}_2\hat{b}_2}} = \frac{.11754}{.08602} = 1.33648, ns$$

$$\frac{\hat{a}_1\hat{b}_1 + \hat{a}_2\hat{b}_2}{s_{\hat{a}_1\hat{b}_1 + \hat{a}_2\hat{b}_2}} = \frac{.47806 + .11754}{.18915} = 3.14882, p < .05$$

### Normal Theory Confidence Limits for Each Specific Mediated Effect

$$\begin{aligned} a_1b_1: \quad LCL_1 &= \hat{a}_1\hat{b}_1 - 1.96(s_{\hat{a}_1\hat{b}_1}) = .47806 - (1.96 * .15948) = .16548 \\ UCL_1 &= \hat{a}_1\hat{b}_1 + 1.96(s_{\hat{a}_1\hat{b}_1}) = .47806 + (1.96 * .15948) = .79065 \end{aligned}$$

*significant,*  
because zero is  
not contained in  
the interval

$$\begin{aligned} a_2b_2: \quad LCL_2 &= \hat{a}_2\hat{b}_2 - 1.96(s_{\hat{a}_2\hat{b}_2}) = .11754 - (1.96 * .08602) = -.05106 \\ UCL_2 &= \hat{a}_2\hat{b}_2 + 1.96(s_{\hat{a}_2\hat{b}_2}) = .11754 + (1.96 * .08602) = .28615 \end{aligned}$$

*non-significant,*  
because zero is  
contained in the  
interval

### Asymmetric Confidence Limits for Each Specific Mediated Effect

$$\begin{aligned} a_1b_1: \quad LCL_1 &= .19889 \\ UCL_1 &= .82199 \end{aligned}$$

$$\begin{aligned} a_2b_2: \quad LCL_2 &= -.02648 \\ UCL_2 &= .31099 \end{aligned}$$

### Are the two mediated effects significantly different from each other?

$$\begin{aligned} s_{\hat{a}_1\hat{b}_1 - \hat{a}_2\hat{b}_2} &= \sqrt{s_{\hat{a}_1}^2 \hat{b}_1^2 + s_{\hat{b}_1}^2 \hat{a}_1^2 + s_{\hat{a}_2}^2 \hat{b}_2^2 + s_{\hat{b}_2}^2 \hat{a}_2^2 - 2\hat{a}_1\hat{a}_2s_{\hat{b}_1\hat{b}_2}} \\ SE \text{ of estimate:} &= \sqrt{(.15796^2)(.56903^2) + (.15681^2)(.84014^2) + (.14602^2)(.52972^2) +} \\ &\quad \sqrt{(.16964^2)(.22190^2) - 2(.84014)(.22190)(.00789)} \\ &= .1729 \end{aligned}$$

$$z\text{-statistic:} \quad \frac{estimate}{se_{estimate}} = \frac{\hat{a}_1\hat{b}_1 - \hat{a}_2\hat{b}_2}{s_{\hat{a}_1\hat{b}_1 - \hat{a}_2\hat{b}_2}} = \frac{.47806 - .11754}{.1729} = 2.0852, p < .05$$

Standard error of  
the difference  
between the two  
mediated effects.

## MPLUS

This output is annotated for your review. Note that although the TECH3 output option used in this example provides you with both covariance and correlation matrices of the parameter estimates, only the covariance matrix is provided for you here to conserve space.

### *Syntax:*

```
Title: CHAPTER 5 Two Mediator Model Example;
```

```
Data:
```

```
Nobs=40;
```

```
File is E:/Chap5_twomed.txt;
```

```
Variable:
```

```
Names are ID X M1 M2 Y;
```

```
Usevariables are X M1 M2 Y;
```

```
Analysis:
```

```
Type is general;
```

```
Estimator is ML;
```

```
Model:
```

```
Y on M1 M2 X;
```

```
M1 on X;
```

```
M2 on X;
```

```
M1 with M2;
```

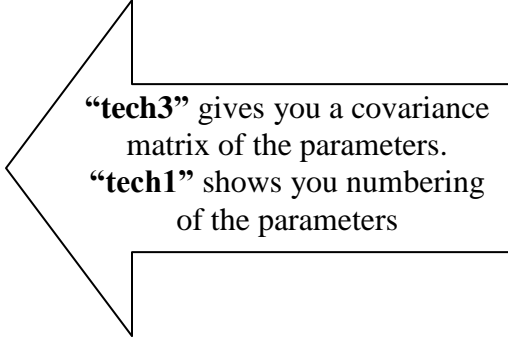
```
X;
```

```
Model Indirect:
```

```
Y ind X;
```

```
Output:
```

```
cinterval tech1 tech3 ;
```



**“tech3”** gives you a covariance matrix of the parameters.  
**“tech1”** shows you numbering of the parameters

*MPlus Output:*

## MODEL RESULTS

		Estimates	S.E.	Est./S.E.	
Y	ON				
M1		0.569	0.149	3.825	$(\hat{b}_1)$
M2		0.530	0.161	3.292	$(\hat{b}_2)$
X		0.112	0.197	0.570	$(\hat{c}')$
M1	ON				
X		0.840	0.154	5.457	$(\hat{a}_1)$
M2	ON				
X		0.222	0.142	1.559	$(\hat{a}_2)$
M1	WITH				
M2		-21.515	11.958	-1.799	
Variances					
X		82.728	18.498	4.472	
Residual Variances					
M1		78.436	17.539	4.472	
M2		67.024	14.987	4.472	
Y		63.321	14.159	4.472	

## TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

	Estimates	S.E.	Est./S.E.	
Effects from X to Y				
Total	0.708	0.169	4.187	$(\hat{a}_1\hat{b}_1 + \hat{a}_2\hat{b}_2) + \hat{c}'$
Total indirect	0.596	0.170	3.499	$(\hat{a}_1\hat{b}_1 + \hat{a}_2\hat{b}_2)$
Specific indirect				
Y				
M1				
X	0.478	0.153	3.132	$(\hat{a}_1\hat{b}_1)$
Y				
M2				
X	0.118	0.083	1.409	$(\hat{a}_2\hat{b}_2)$

Direct				
Y				
X	0.112	0.197	0.570	( $\hat{c}'$ )

## CONFIDENCE INTERVALS OF MODEL RESULTS

		Lower .5%	Lower 2.5%	Estimates	Upper 2.5%	Upper .5%
Y	ON					
M1		0.186	0.277	0.569	0.861	0.952
M2		0.115	0.214	0.530	0.845	0.944
X		-0.394	-0.273	0.112	0.498	0.619
M1	ON					
X		0.444	0.538	0.840	1.142	1.237
M2	ON					
X		-0.145	-0.057	0.222	0.501	0.588
M1	WITH					
M2		-52.317	-44.953	-21.515	1.923	9.287
Variances						
X		35.079	46.471	82.728	118.984	130.376
Residual Variances						
M1		33.259	44.060	78.436	112.812	123.612
M2		28.420	37.649	67.024	96.398	105.627
Y		26.850	35.569	63.321	91.072	99.791

## TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

	Lower .5%	Lower 2.5%	Estimates	Upper 2.5%	Upper .5%
Effects from X to Y					
Total	0.272	0.376	0.708	1.039	1.143
Total indirect	0.157	0.262	0.596	0.929	1.034
Specific indirect					
Y					
M1					
X	0.085	0.179	0.478	0.777	0.871
Y					
M2					
X	-0.097	-0.046	0.118	0.281	0.332
Direct					
Y					
X	-0.394	-0.273	0.112	0.498	0.619



## TECHNICAL 1 OUTPUT

## PARAMETER SPECIFICATION

	LAMBDA			
	M1	M2	Y	X
M1	0	0	0	0
M2	0	0	0	0
Y	0	0	0	0
X	0	0	0	0

	THETA			
	M1	M2	Y	X
M1	0			
M2	0	0		
Y	0	0	0	
X	0	0	0	0

	BETA			
	M1	M2	Y	X
M1	0	0	0	1
M2	0	0	0	2
Y	3	4	0	5
X	0	0	0	0

	PSI			
	M1	M2	Y	X
M1	6			
M2	7	8		
Y	0	0	9	
X	0	0	0	10

## STARTING VALUES

	LAMBDA			
	M1	M2	Y	X
M1	1.000	0.000	0.000	0.000
M2	0.000	1.000	0.000	0.000
Y	0.000	0.000	1.000	0.000
X	0.000	0.000	0.000	1.000



## SPSS

### *Syntax:*

```
data list free
  / s x m1 m2 y.
begin data
  1  51  41  54  59
  2  40  34  51  60
  .
end data.
```

```
*Equation 5.1.
regression
/variables=x y m1 m2
/dependent=y
/enter=x.
```

```
* Equation 5.2.
regression
/variables=x y m1 m2
/statistics=defaults bcov
/dependent=y
/enter= x m1 m2.
```

```
* Equation 5.3.
regression
/variables=x y m1
/dependent=m1
/enter=x.
```

```
*Equation 5.4.
regression
/variables=x y m2
/dependent=m2
/enter=x.
```

SPSS Output:

## Regression

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	34.727	8.925		3.891	.000
	x	.708	.173	.552	4.081	.000

a. Dependent Variable: y

## Regression

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.123	10.478		.871	.390
	x	.112	.207	.087	.541	.592
	m1	.569	.157	.571	3.629	.001
	m2	.530	.170	.383	3.123	.004

a. Dependent Variable: y

**Coefficient Correlations<sup>a</sup>**

Model			m2	m1	x
1	Correlations	m2	1.000	.297	-.370
		m1	.297	1.000	-.689
		x	-.370	-.689	1.000
	Covariances	m2	.029	.008	-.013
		m1	.008	.025	-.022
		x	-.013	-.022	.043

a. Dependent Variable: y

## Regression

**Coefficients<sup>a</sup>**

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	7.097	8.129		.873	.388
x	.840	.158	.653	5.319	.000

a. Dependent Variable: m1

## Regression

**Coefficients<sup>a</sup>**

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	40.711	7.514		5.418	.000
x	.222	.146	.239	1.520	.137

a. Dependent Variable: m2