

Online Appendix to accompany “Investigating multilevel mediation with fully or partially nested data”

Contents:

- A. Scalar equations for the fully nested MSEM example (example 1)
- B. Scalar equations for the partially nested MSEM-PN example (example 2)
- C. *Mplus* fully nested syntax
- D. *Mplus* fully nested output
- E. *Mplus* partially nested syntax
- F. *Mplus* partially nested output
- G. Monte Carlo R syntax for all confidence intervals

Section A: Scalar equations for the fully nested MSEM example (example 1)

This section of the online appendix details the scalar MSEM equations for the fully nested simulated example described in the text. TP_{ij} corresponds to the dependent variable team performance, CTC_{ij} to the mediator commitment to change, PC_{ij} to the mediator perceived charisma, and CPB_{ij} is the independent variable change promoting behavior. Corresponding to equations 6, 7, and 8 in the text:

$$\begin{aligned} TP_j &= \widetilde{TP}_j \\ CTC_{ij} &= \widetilde{CTC}_{ij} + \widetilde{CTC}_j \\ PC_{ij} &= \widetilde{PC}_{ij} + \widetilde{PC}_j \\ CPB_{ij} &= \widetilde{CPB}_{ij} + \widetilde{CPB}_j \end{aligned}$$

Between:

$$\begin{aligned} \widetilde{TP}_j &= b_0^{TP} + b_{1B}^{TP} \widetilde{CTC}_j + \zeta_j^{TP} \\ \widetilde{CTC}_j &= b_0^{CTC} + b_{1B}^{CTC} \widetilde{PC}_j + \zeta_j^{CTC} \\ \widetilde{PC}_j &= b_0^{PC} + b_{1B}^{PC} \widetilde{CPB}_j + \zeta_j^{PC} \\ \widetilde{CPB}_j &= b_0^{CPB} + \zeta_j^{CPB} \end{aligned}$$

Within:

$$\begin{aligned} \widetilde{CTC}_{ij} &= b_{1W}^{CTC} \widetilde{PC}_{ij} + \varepsilon_{ij}^{CTC} \\ \widetilde{PC}_{ij} &= b_{1W}^{PC} \widetilde{CPB}_{ij} + \varepsilon_{ij}^{PC} \\ \widetilde{CPB}_{ij} &= \varepsilon_{ij}^{CPB} \end{aligned}$$

where:

$$\begin{aligned} \begin{bmatrix} \zeta_j^{TP} \\ \zeta_j^{CTC} \\ \zeta_j^{PC} \\ \zeta_j^{CPB} \end{bmatrix} &\sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi^{TP} & & & \\ 0 & \psi^{CTC} & & \\ 0 & 0 & \psi^{PC} & \\ 0 & 0 & 0 & \psi^{CPB} \end{bmatrix} \right) \\ \begin{bmatrix} \varepsilon_{ij}^{CTC} \\ \varepsilon_{ij}^{PC} \\ \varepsilon_{ij}^{CPB} \end{bmatrix} &\sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \theta_\varepsilon^{CTC} & & \\ 0 & \theta_\varepsilon^{PC} & \\ 0 & 0 & \theta_\varepsilon^{CPB} \end{bmatrix} \right) \end{aligned}$$

Section B: Scalar equations for the partially nested MSEM example (example 2)

Clustered arm:

$$\begin{aligned} TP_j &= \widetilde{TP}_j^c \\ CTC_{ij} &= \widetilde{CTC}_{ij}^c + \widetilde{CTC}_j^c \\ PC_{ij} &= \widetilde{PC}_{ij}^c + \widetilde{PC}_j^c \\ CPB_{ij} &= \widetilde{CPB}_{ij}^c + \widetilde{CPB}_j^c \end{aligned}$$

Between:

$$\begin{aligned} \widetilde{TP}_j^c &= b_0^{TPc} + b_{1B}^{TPc} \widetilde{CTC}_j^c + \zeta_j^{TPc} \\ \widetilde{CTC}_j^c &= b_0^{CTCc} + b_{1B}^{CTCc} \widetilde{PC}_j^c + \zeta_j^{CTCc} \\ \widetilde{PC}_j^c &= b_0^{PCc} + b_{1B}^{PCc} \widetilde{CPB}_j^c + \zeta_j^{PCc} \\ \widetilde{CPB}_j^c &= b_0^{CPBc} + \zeta_j^{CPBc} \end{aligned}$$

Within:

$$\begin{aligned} \widetilde{CTC}_{ij}^c &= b_{1W}^{CTCc} \widetilde{CPB}_{ij}^c + b_{2W}^{CTCc} \widetilde{PC}_{ij}^c + \varepsilon_{ij}^{CTCc} \\ \widetilde{PC}_{ij}^c &= b_{1W}^{PCc} \widetilde{CPB}_{ij}^c + \varepsilon_{ij}^{PCc} \\ \widetilde{CPB}_{ij}^c &= \varepsilon_{ij}^{CPBc} \end{aligned}$$

where:

$$\begin{aligned} \begin{bmatrix} \zeta_j^{TPc} \\ \zeta_j^{CTCc} \\ \zeta_j^{PCc} \\ \zeta_j^{CPBc} \end{bmatrix} &\sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi^{TPc} & & & \\ 0 & \psi^{CTCc} & & \\ 0 & 0 & \psi^{PCc} & \\ 0 & 0 & 0 & \psi^{CPBc} \end{bmatrix} \right) \\ \begin{bmatrix} \varepsilon_{ij}^{CTCc} \\ \varepsilon_{ij}^{PCc} \\ \varepsilon_{ij}^{CPBc} \end{bmatrix} &\sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \theta_\varepsilon^{CTCc} & & \\ 0 & \theta_\varepsilon^{PCc} & \\ 0 & 0 & \theta_\varepsilon^{CPBc} \end{bmatrix} \right) \end{aligned}$$

Unclassified arm (each person is their own cluster):

$$\begin{aligned} TP_j &= \widetilde{TP}_j^u \\ CTC_{ij} &= \widetilde{CTC}_{ij}^u + \widetilde{CTC}_j^u \\ PC_{ij} &= \widetilde{PC}_{ij}^u + \widetilde{PC}_j^u \\ CPB_{ij} &= \widetilde{CPB}_{ij}^u + \widetilde{CPB}_j^u \end{aligned}$$

$$\begin{aligned} \widetilde{TP}_j^u &= b_0^{TPu} + b_{1B}^{TPu} \widetilde{CTC}_j^u + \zeta_j^{TPu} \\ \widetilde{CTC}_j^u &= b_0^{CTCu} + b_{1B}^{CTCu} \widetilde{PC}_j^u + \zeta_j^{CTCu} \\ \widetilde{PC}_j^u &= b_0^{PCu} + b_{1B}^{PCu} \widetilde{CPB}_j^u + \zeta_j^{PCu} \\ \widetilde{CPB}_j^u &= b_0^{CPBu} + \zeta_j^{CPBu} \end{aligned}$$

$$\begin{aligned} \widetilde{CTC}_{ij}^u &= 0 \\ \widetilde{PC}_{ij}^u &= 0 \\ \widetilde{CPB}_{ij}^u &= 0 \end{aligned}$$

$$\begin{bmatrix} \zeta_j^{TPu} \\ \zeta_j^{CTCu} \\ \zeta_j^{PCu} \\ \zeta_j^{CPBu} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi^{TPu} & & & \\ 0 & \psi^{CTCu} & & \\ 0 & 0 & \psi^{PCu} & \\ 0 & 0 & 0 & \psi^{CPBu} \end{bmatrix} \right)$$

Section C: *Mplus* fully nested syntax

```
DATA: FILE IS fullynest_seed100.dat; !call dataset
VARIABLE:
NAMES ARE TP PC CTC CPB CLUSTER; !name variables
USEVARIABLES ARE TP PC CTC CPB; !variables to be used in analysis
CLUSTER=CLUSTER; !identify clustering variable
BETWEEN ARE TP; !identify between-cluster (level-2) variables
ANALYSIS: TYPE IS TWOLEVEL;
MODEL:
%WITHIN% !within-cluster (level-1) model
PC CTC CPB; !estimate within-cluster variances
CTC ON PC (bw); !regress CTC on PC, call the slope "bw"
PC ON CPB (aw); !regress PC on CPB, call the slope "aw"
%BETWEEN% !between-group (level-2) model
CPB PC CTC TP; !estimate between-cluster variances
PC ON CPB (ab); !regress PC on CPB, call the slope "ab"
CTC ON PC (bb); !regress CTC on PC, call the slope "bb"
TP ON CTC (cb); !regress CTC on TP, call the slope "cb"
[CPB TP PC CTC]; !estimate variable means

MODEL CONSTRAINT:
NEW(indb_3 indb_2 indw_2 diff); !create indirect effect parameters
indb_3=ab*bb*cb; !between-cluster indirect effect 1
indb_2=ab*bb; !between-cluster indirect effect 2
indw_2=aw*bw; !within-cluster indirect effect
diff=indb_2-indw_2; !diff. of within- and between-cluster indirect effects

OUTPUT: TECH1 TECH3 SVALUES;
```

Section D: *Mplus* fully nested output

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	142
Number of dependent variables	3
Number of independent variables	1
Number of continuous latent variables	0

Observed dependent variables

Continuous

TP	PC	CTC
----	----	-----

Observed independent variables

CPB

Variables with special functions

Cluster variable	CLUSTER
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Between variables

TP

Estimator	MLR
Information matrix	OBSERVED
Maximum number of iterations	100
Convergence criterion	0.100D-05
Maximum number of EM iterations	500
Convergence criteria for the EM algorithm	
Loglikelihood change	0.100D-02
Relative loglikelihood change	0.100D-05
Derivative	0.100D-03
Minimum variance	0.100D-03
Maximum number of steepest descent iterations	20
Maximum number of iterations for H1	2000
Convergence criterion for H1	0.100D-03
Optimization algorithm	EMA

Input data file(s)
 fullynest_seed100.dat
Input data format FREE

SUMMARY OF DATA

Number of clusters	33
Average cluster size	4.303

Estimated Intraclass Correlations for the Y Variables

Variable	Intraclass Correlation	Variable	Intraclass Correlation	Variable	Intraclass Correlation
PC	0.588	CTC	0.203	CPB	0.510

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters 16

Loglikelihood

H0 Value	-498.701
H0 Scaling Correction Factor for MLR	0.9223
H1 Value	-494.147
H1 Scaling Correction Factor for MLR	0.8396

Information Criteria

Akaike (AIC)	1029.401
Bayesian (BIC)	1076.695
Sample-Size Adjusted BIC	1026.070
(n* = (n + 2) / 24)	

Chi-Square Test of Model Fit

Value	17.900*
Degrees of Freedom	4
P-Value	0.0013
Scaling Correction Factor for MLR	0.5088

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.156
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CFI/TLI

CFI	0.917
TLI	0.814

Chi-Square Test of Model Fit for the Baseline Model

Value	177.445
Degrees of Freedom	9
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value for Within	0.057
Value for Between	0.081

MODEL RESULTS

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level					
CTC	ON				
PC		0.362	0.148	2.444	0.015
PC	ON				
CPB		0.375	0.041	9.241	0.000
Variances					
CPB		0.707	0.079	9.000	0.000
Residual Variances					
PC		0.150	0.018	8.534	0.000
CTC		0.649	0.081	8.009	0.000
Between Level					
PC	ON				
CPB		0.455	0.133	3.413	0.001
CTC	ON				
PC		0.656	0.151	4.344	0.000
TP	ON				
CTC		0.602	0.259	2.326	0.020

Means				
CPB	3.916	0.167	23.449	0.000
Intercepts				
TP	5.409	2.493	2.170	0.030
PC	3.321	0.555	5.988	0.000
CTC	6.308	0.790	7.985	0.000
Variances				
CPB	0.793	0.181	4.373	0.000
Residual Variances				
TP	0.249	0.068	3.649	0.000
PC	0.192	0.041	4.681	0.000
CTC	0.008	0.024	0.312	0.755
New/Additional Parameters				
INDB_3	0.180	0.076	2.368	0.018
INDB_2	0.299	0.121	2.466	0.014
INDW_2	0.136	0.057	2.382	0.017
DIFF	0.163	0.138	1.178	0.239

Section E: *Mplus* partially nested syntax

```

DATA: FILE IS bothnest_seed100.dat;
VARIANCES=NOCHECK;

VARIABLE: NAMES ARE TP PC CTC CPB CLUSTER treat; !name variables
USEVARIABLES ARE TP PC CTC CPB; !identify variables for analysis
CLUSTER IS cluster; !identify clustering variable
GROUPING IS treat (0=cont 1=txt); !identify grouping (study arm) variable
BETWEEN IS tp; !identify between-cluster (level-2) variables
ANALYSIS: TYPE IS TWOLEVEL;

MODEL: !model for tx (nested) group
%WITHIN% !within-cluster (level-1) model for tx group
PC CTC CPB; !estimate within-cluster variances
CTC ON PC (bw); !regress CTC on PC, call the slope "bw"
PC ON CPB (aw); !regress PC on CPB, call the slope "aw"

%BETWEEN% !between-cluster (level-2) model for tx group
CPB PC CTC TP; !estimate between-cluster variances
PC ON CPB (ab); !regress PC on CPB, call the slope "ab"
CTC ON PC (bb); !regress CTC on PC, call the slope "bb"
TP ON CTC (cb); !regress TP on CTC, call the slope "cb"
[CPB TP PC CTC]; !estimate means

MODEL cont: !model for control (non-nested) group
%WITHIN% !within-cluster (level-1) model for control group
PC@0; CTC@0; CPB@0; !all variances set to 0
CTC ON PC@0; !regression of CTC on PC set to 0
PC ON CPB@0; !regression of PC on CPB set to 0

%BETWEEN% !between-cluster (level-2) model for control group
CPB PC CTC TP; !estimate between-cluster variances

```

```

PC ON CPB (a); !regress PC on CPB, call the slope "a"
CTC ON PC (b); !regress CTC on PC, call the slope "b"
TP ON CTC (c); !regress TP on CTC, call the slope "c"
[CPB TP PC CTC]; !estimate means

MODEL CONSTRAINT:
!create indirect effect variables
NEW(indb_3 indb_2 indw_2 diff inds_3 inds_2 diff3_arm diff2_arm);
indb_3=ab*bb*cb; !first between-cluster indirect effect for tx group
indb_2=ab*bb; !second between-cluster indirect effect for tx group
indw_2=aw*bw; !within-cluster indirect effect for tx group
diff=indb_2-indw_2; !diff. in within- and between-cluster
                    !indirect effects for tx group

inds_3=a*b*c; !first indirect effect for control group
inds_2=a*b; !second indirect effect for control group
diff3_arm=indb_3-inds_3; !diff. in first indirect effect
                    !across tx and control groups
diff2_arm=indw_2-inds_2; !diff. in second indirect effect
                    !across tx and control groups

OUTPUT: NOCHISQUARE TECH1 TECH3 SVALUES;

```

Section F: *Mplus* partially nested output

SUMMARY OF ANALYSIS

Number of groups	2
Number of observations	
Group CONT	142
Group TXT	142
Total sample size	284

Number of dependent variables	3
Number of independent variables	1
Number of continuous latent variables	0

Observed dependent variables

Continuous			
TP	PC	CTC	

Observed independent variables

 CPB

Variables with special functions

Grouping variable	TREAT
Cluster variable	CLUSTER

Between variables

 TP

Estimator

MLR

Information matrix	OBSERVED
Maximum number of iterations	100
Convergence criterion	0.100D-05
Maximum number of EM iterations	500
Convergence criteria for the EM algorithm	
Loglikelihood change	0.100D-02
Relative loglikelihood change	0.100D-05
Derivative	0.100D-03
Minimum variance	0.100D-03
Maximum number of steepest descent iterations	20
Maximum number of iterations for H1	2000
Convergence criterion for H1	0.100D-03
Optimization algorithm	EMA

Input data file(s)
 bothnest_seed100.dat
Input data format FREE

SUMMARY OF DATA

Group CONT	
Number of clusters	142
Group TXT	
Number of clusters	33

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters	27
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Loglikelihood

H0 Value	-1126.689
H0 Scaling Correction Factor for MLR	0.9653

Information Criteria

Akaike (AIC)	2307.377
Bayesian (BIC)	2405.900
Sample-Size Adjusted BIC ($n^* = (n + 2) / 24$)	2320.282

MODEL RESULTS

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group CONT					
Within Level					
CTC	ON				
PC		0.000	0.000	999.000	999.000
PC	ON				

CPB		0.000	0.000	999.000	999.000
Variances					
CPB		0.000	0.000	999.000	999.000
Residual Variances					
PC		0.000	0.000	999.000	999.000
CTC		0.000	0.000	999.000	999.000
Between Level					
PC	ON				
CPB		0.357	0.043	8.221	0.000
CTC	ON				
PC		0.295	0.100	2.938	0.003
TP	ON				
CTC		0.185	0.056	3.322	0.001
Means					
CPB		3.943	0.095	41.366	0.000
Intercepts					
TP		4.453	0.419	10.629	0.000
PC		3.656	0.174	20.995	0.000
CTC		5.941	0.519	11.441	0.000
Variances					
CPB		1.290	0.170	7.590	0.000
Residual Variances					
TP		0.315	0.040	7.884	0.000
PC		0.276	0.033	8.447	0.000
CTC		0.727	0.075	9.733	0.000
Group TXT					
Within Level					
CTC	ON				
PC		0.362	0.148	2.444	0.015
PC	ON				
CPB		0.375	0.041	9.241	0.000
Variances					
CPB		0.707	0.079	9.000	0.000
Residual Variances					
PC		0.150	0.018	8.534	0.000
CTC		0.649	0.081	8.009	0.000
Between Level					
PC	ON				
CPB		0.455	0.133	3.413	0.001

CTC	ON				
PC		0.656	0.151	4.344	0.000
TP	ON				
CTC		0.602	0.259	2.326	0.020
Means					
CPB		3.916	0.167	23.449	0.000
Intercepts					
TP		5.409	2.493	2.170	0.030
PC		3.321	0.555	5.988	0.000
CTC		6.308	0.790	7.985	0.000
Variances					
CPB		0.793	0.181	4.373	0.000
Residual Variances					
TP		0.249	0.068	3.649	0.000
PC		0.192	0.041	4.681	0.000
CTC		0.008	0.024	0.312	0.755
New/Additional Parameters					
INDB_3		0.180	0.076	2.368	0.018
INDB_2		0.299	0.121	2.466	0.014
INDW_2		0.136	0.057	2.382	0.017
DIFF		0.163	0.138	1.178	0.239
INDS_3		0.019	0.009	2.222	0.026
INDS_2		0.105	0.038	2.788	0.005
DIFF3_AR		0.160	0.076	2.097	0.036
DIFF2_AR		0.031	0.068	0.448	0.654

Section G: Monte Carlo CI R syntax

#example 1, between indirect effect (2 paths)

```
require(MASS) #load required package
a=.455 #assign estimated values to parameters
b=.656
rep=10000000 #CI to be based on ten million reps
conf=95      #95% CI
pest <- c(a,b) #put estimates into a vector
#create 2x2 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.17810755E-01, 0.38238370E-02,
  0.38238370E-02, 0.22770649E-01),2,2)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)
ieb <- mcmc[,1]*mcmc[,2] #define indirect effect
low=(1-conf/100)/2
upp=((1-conf/100)/2)+(conf/100)
LL=quantile(ieb,low) #find lower confidence limit
UL=quantile(ieb,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b,LL,UL)) #print the output
#make a histogram
hist(ieb,breaks='FD',col='skyblue',
     xlab=paste(conf,'% Confidence Interval ', 'LL',LL4,' UL',UL4),
     main='Distribution of Indirect Effect')
```

#example 1, within indirect effect (2 paths)

```
require(MASS) #load required package
a=.375 #assign estimated values to parameters
b=.362
rep=10000000 #CI to be based on ten million reps
conf=95      #95% CI
pest <- c(a,b) #put estimates into a vector
#create 2x2 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.16491521E-02, -0.18865290E-03,
  -0.18865290E-03, 0.21896878E-01),2,2)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)
iew <- mcmc[,1]*mcmc[,2] #define indirect effect
low=(1-conf/100)/2
upp=((1-conf/100)/2)+(conf/100)
LL=quantile(iew,low) #find lower confidence limit
UL=quantile(iew,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b,LL,UL)) #print the output
#make a histogram
hist(iew,breaks='FD',col='skyblue',
```

```
xlab=paste(conf,'% Confidence Interval ','LL',LL4,' UL',UL4),
main='Distribution of Indirect Effect')
```

example 1, difference of B and W indirect effects

```
require(MASS) #load required package
a=.455 #assign estimated values to parameters
b=.656
c=.375
d=.362
rep=10000000 #CI to be based on ten million reps
conf=95 #95% CI
pest <- c(a,b,c,d) #put estimates into a vector
#create 4x4 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.17810755E-01, 0.38238370E-02, -0.30266999E-02, -0.89393417E-04,
  0.38238370E-02, 0.22770649E-01, 0.10262729E-03, 0.68648195E-03,
-0.30266999E-02, 0.10262729E-03, 0.16491521E-02, -0.18865290E-03,
-0.89393417E-04, 0.68648195E-03, -0.18865290E-03, 0.21896878E-01
),4,4)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)
#define indirect effect difference
iediff <- mcmc[,1]*mcmc[,2]-mcmc[,3]*mcmc[,4]
low=(1-conf/100)/2
upp=((1-conf/100)/2)+(conf/100)
LL=quantile(iediff,low) #find lower confidence limit
UL=quantile(iediff,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b-c*d,LL,UL)) #print the output
#make a histogram
hist(iediff,breaks='FD',col='skyblue',
xlab=paste(conf,'% Confidence Interval ','LL',LL4,' UL',UL4),
main='Distribution of Indirect Effect Difference')
```

example 1, between indirect effect (3 paths)

```
require(MASS) #load required package
a=.455 #assign estimated values to parameters
b=.656
c=.602
rep=10000000 #CI to be based on ten million reps
conf=95 #95% CI
pest <- c(a,b,c) #put estimates into a vector
#create 3x3 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.17810755E-01, 0.38238370E-02, -0.85890777E-02,
  0.38238370E-02, 0.22770649E-01, -0.21358784E-01,
-0.85890777E-02, -0.21358784E-01, 0.66926164E-01),3,3)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)
ieb <- mcmc[,1]*mcmc[,2]*mcmc[,3] #define indirect effect
low=(1-conf/100)/2
```

```

upp=((1-conf/100)/2)+(conf/100)
LL=quantile(ieb,low) #find lower confidence limit
UL=quantile(ieb,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b*c,LL,UL)) #print the output
#make a histogram
hist(ieb,breaks='FD',col='skyblue',
     xlab=paste(conf,'% Confidence Interval ','LL',LL4,' UL',UL4),
     main='Distribution of Indirect Effect')

```

example 2, between indirect effect (2 paths)

```

require(MASS) #load required package
a=.357 #assign estimated values to parameters
b=.295
rep=10000000 #CI to be based on ten million reps
conf=95      #95% CI
pest <- c(a,b) #put estimates into a vector
#create 2x2 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.188400E-02, -0.106188E-03,
-0.106188E-03,  0.100600E-01),2,2)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)
ieb <- mcmc[,1]*mcmc[,2] #define indirect effect
low=(1-conf/100)/2
upp=((1-conf/100)/2)+(conf/100)
LL=quantile(ieb,low) #find lower confidence limit
UL=quantile(ieb,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b,LL,UL)) #print the output
#make a histogram
hist(ieb,breaks='FD',col='skyblue',
     xlab=paste(conf,'% Confidence Interval ','LL',LL4,' UL',UL4),
     main='Distribution of Indirect Effect')

```

example 2, between indirect effect (3 paths)

```

require(MASS) #load required package
a=.357 #assign estimated values to parameters
b=.295
c=.185
rep=10000000 #CI to be based on ten million reps
conf=95      #95% CI
pest <- c(a,b,c) #put estimates into a vector
#create 3x3 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.188400E-02, -0.106188E-03, -0.447846E-04,
-0.106188E-03,  0.100600E-01, -0.418114E-03,
-0.447846E-04, -0.418114E-03,  0.310931E-02),3,3)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)

```

```

ieb <- mcmc[,1]*mcmc[,2]*mcmc[,3] #define indirect effect
low=(1-conf/100)/2
upp=((1-conf/100)/2)+(conf/100)
LL=quantile(ieb,low) #find lower confidence limit
UL=quantile(ieb,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b*c,LL,UL)) #print the output
#make a histogram
hist(ieb,breaks='FD',col='skyblue',
     xlab=paste(conf,'% Confidence Interval ','LL',LL4,' UL',UL4),
     main='Distribution of Indirect Effect')

```

example 2, difference of B indirect effects

```

require(MASS) #load required package
a=.455 #assign estimated values to parameters
b=.656
c=.602
d=.357
e=.295
f=.185
rep=10000000 #CI to be based on ten million reps
conf=95      #95% CI
pest <- c(a,b,c,d,e,f) #put estimates into a vector
#create 6x6 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.178107E-01,  0.382340E-02, -0.858833E-02,  0,  0,  0,
  0.382340E-02,  0.227697E-01, -0.213564E-01,  0,  0,  0,
-0.858833E-02, -0.213564E-01,  0.669208E-01,  0,  0,  0,
  0,  0,  0,  0.188400E-02, -0.106188E-03, -0.447846E-04,
  0,  0,  0, -0.106188E-03,  0.100600E-01, -0.418114E-03,
  0,  0,  0, -0.447846E-04, -0.418114E-03,  0.310931E-02),6,6)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)
#define indirect effect difference
iediff <- mcmc[,1]*mcmc[,2]*mcmc[,3]-mcmc[,4]*mcmc[,5]*mcmc[,6]
low=(1-conf/100)/2
upp=((1-conf/100)/2)+(conf/100)
LL=quantile(iediff,low) #find lower confidence limit
UL=quantile(iediff,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b*c-d*e*f,LL,UL)) #print the output
#make a histogram
hist(iediff,breaks='FD',col='skyblue',
     xlab=paste(conf,'% Confidence Interval ','LL',LL4,' UL',UL4),
     main='Distribution of Indirect Effect Difference')

```

example 2, difference of unclustered and W indirect effects

```

require(MASS) #load required package
a=.375 #assign estimated values to parameters
b=.362

```

```

c=.357
d=.295
rep=10000000 #CI to be based on ten million reps
conf=95      #95% CI
pest <- c(a,b,c,d) #put estimates into a vector
#create 4x4 acov matrix from tech3 output in Mplus
acov <- matrix(c(
  0.16491521E-02, -0.18865290E-03, 0, 0,
-0.18865290E-03,  0.21896878E-01, 0, 0,
  0, 0,  0.188400E-02, -0.106188E-03,
  0, 0, -0.106188E-03,  0.100600E-01),4,4)
#generate MVN parameter distribution
mcmc <- mvrnorm(rep,pest,acov,empirical=FALSE)
#define indirect effect difference
iediff <- mcmc[,1]*mcmc[,2]-mcmc[,3]*mcmc[,4]
low=(1-conf/100)/2
upp=((1-conf/100)/2)+(conf/100)
LL=quantile(iediff,low) #find lower confidence limit
UL=quantile(iediff,upp) #find upper confidence limit
LL4=format(LL,digits=4) #round to 4 places
UL4=format(UL,digits=4) #round to 4 places
print(c(a*b-c*d,LL,UL)) #print the output
#make a histogram
hist(iediff,breaks='FD',col='skyblue',
  xlab=paste(conf,'% Confidence Interval ', 'LL',LL4,' UL',UL4),
  main='Distribution of Indirect Effect Difference')

```