14 Mplus inputs

14.1 Mplus input for simulation of continuous M and continuous Y with treatment-mediator interaction

[Table 25 about here.]

[Table 26 about here.]

14.2 Mplus input for simulation of binary outcome and continuous mediator

[Table 27 about here.]

[Table 28 about here.]

[Table 29 about here.]

[Table 30 about here.]

14.3 Mplus input for aggression example

[Table 31 about here.]

[Table 32 about here.]

[Table 33 about here.]

14.4 Mplus input for smoking example

[Table 34 about here.]

[Table 35 about here.]

14.5 Mplus input for Pearl's artificial example

[Table 36 about here.]

[Table 37 about here.]

[Table 38 about here.]

[Table 39 about here.]

[Table 40 about here.]

[Table 41 about here.]

[Table 42 about here.]

[Table 43 about here.]

14.6 Mplus input for n=200 data drawn on the Pearl example

[Table 44 about here.]

[Table 45 about here.]

14.7 Mplus input for Monte Carlo simulation of a nominal mediator and a continuous outcome

[Table 46 about here.]

[Table 47 about here.]

[Table 48 about here.]

[Table 49 about here.]

14.8 Mplus input for hypothetical pollution data with a nominal mediator and a binary outcome

[Table 50 about here.]

[Table 51 about here.]

14.9 Mplus input for count outcome simulation

[Table 52 about here.]

[Table 53 about here.]

[Table 54 about here.]

14.10 Mplus input for sensitivity analysis

14.10.1 Regular mediation with $\rho = 0$

[Table 55 about here.]

14.10.2 Sensitivity analysis with $\rho = 0.25$

[Table 56 about here.]

14.10.3 Analysis of head circumference

[Table 57 about here.]

Table 25: Input for step 1 y on xm

```
TITLE:        Simulating x-m interaction effect on y using a random
              slope, saving the data for external Monte Carlo analysis
MONTECARLO:
              NAMES = y m x;
              NOBSERVATION = 400;
              NREPS = 500;
              REPSAVE = ALL;
              SAVE = xmrep*.dat;
              CUTPOINTS = x(0);
MODEL POPULATION:
              x@1;
              [y*1];
              y ON x*.4;
              beta1 | y ON m;
              beta1 ON x*.2;
              [beta1*.5];
              beta1@0;
              [m*2];
              m ON x*.5;
              y*.5;
              m*1;
ANALYSIS:     TYPE = RANDOM;
MODEL:        [y*1] (beta0);
              y ON x*.4 (beta2);
              beta1 | y ON m;
              beta1 ON x*.2 (beta3);
              [beta1*.5] (beta1);
              beta1@0;
              [m*2] (gamma0);
              m ON x*.5 (gamma1);
              y*.5;
              m*1;
MODEL CONSTRAINT:
              NEW(tie*.35 pie*.25 de*.8);
              tie=beta1*gamma1+beta3*gamma1;
              pie=beta1*gamma1;
              de=beta2+beta3*gamma0;
```

Table 26: Input for step 2 y on xm

TITLE:	Simulating x-m interaction effect on y using a random slope, Step 2: External Monte Carlo analysis
DATA:	FILE = xmreplist.dat;
	TYPE = MONTECARLO;
VARIABLE:	NAMES = y m x;
	USEVARIABLES = y m x xm;
DEFINE:	xm = x*m;
ANALYSIS:	
MODEL:	[y*1] (beta0);
	y ON x*.4 (beta2);
	y ON xm (beta3);
	y ON m*.5 (beta1);
	[m*2] (gamma0);
	m ON x*.5 (gamma1);
	y*.5;
	m*1;
MODEL CONSTRAINT:	
	NEW(tie*.35 pie*.25 de*.8);
	tie=beta1*gamma1+beta3*gamma1;
	pie=beta1*gamma1;
	de=beta2+beta3*gamma0;

Table 27: Input for step 1 ML y on xm n=200

```
TITLE:        Simulating x-m interaction effect on y using a random
              slope, saving the data for external Monte Carlo analysis:
              Binary Y, continuous M
MONTECARLO:
              NAMES = y m x;
              GENERATE = y(1 p);
              CATEGORICAL = y;
              NOBSERVATION = 200;
              NREPS = 500;
              REPSAVE = ALL;
              SAVE = n200xmrep*.dat;
              CUTPOINTS = x(0);
MODEL POPULATION:
              x@1;
              [y$1*.5];
              y ON x*.3;
              beta1 | y ON m;
              beta1 ON x*.2;
              [beta1*.7];
              beta1@0;
              [m*.5];
              m ON x*.5;
              m*.75;
ANALYSIS:     TYPE = RANDOM;
              ESTIMATOR = ML;
              LINK = PROBIT;
MODEL:        [y$1*.5] (beta0);
              y ON x*.3 (beta2);
              beta1 | y ON m;
              beta1 ON x*.2 (beta3);
              [beta1*.7] (beta1);
              beta1@0;
              [m*.5] (gamma0);
              m ON x*.5 (gamma1);
              m*.75;
MODEL CONSTRAINT:
              NEW(ind*.45 dir*.4);
              ind=beta1*gamma1+beta3*gamma1;
              dir=beta3*gamma0+beta2;
```

Table 28: Input for step 2 ML y on xm n=200

TITLE:	Simulating x-m interaction effect on y using a random slope Step 2 Binary Y, continuous M
DATA:	FILE = n200xmreplist.dat; TYPE = MONTECARLO;
VARIABLE:	NAMES = y m x; USEVARIABLES = y m x xm; CATEGORICAL = y;
DEFINE:	xm = x*m;
ANALYSIS:	ESTIMATOR = ML; LINK = PROBIT;
MODEL:	[y$1*.5] (mbeta0); y ON x*.3 (mbeta2); y ON m*.7 (beta1); y ON xm*.2 (beta3); [m*.5] (gamma0); m ON x*.5 (gamma1); m*.75 (sig2);
MODEL CONSTRAINT:	

	NEW(ind*.45 dir*.4 arg11*.7 arg10*.25 arg01*.2 arg00*-.15 v1*1.6075 v0*1.3675 probit11*.5521 probit10*.1972 probit01*.17103 probit00*-.1283 tie*.131 de*.129 pie*.119);
	dir=beta3*gamma0+beta2;
	ind=beta1*gamma1+beta3*gamma1;
	arg11=-mbeta0+beta2+(beta1+beta3)*(gamma0+gamma1);
	arg10=-mbeta0+beta2+(beta1+beta3)*gamma0;
	arg01=-mbeta0+beta1*(gamma0+gamma1);
	arg00=-mbeta0+beta1*gamma0;
	v1=(beta1+beta3)∧2*sig2+1;
	v0=beta1∧2*sig2+1;
	probit11=arg11/sqrt(v1);
	probit10=arg10/sqrt(v1);
	probit01=arg01/sqrt(v0);
	probit00=arg00/sqrt(v0);
	! Phi function needed below:
	tie=phi(probit11)-phi(probit10);
	de=phi(probit10)-phi(probit00);
	pie=phi(probit01)-phi(probit00);

Table 29: Input excerpts for step 2 bayes y on xm n=200

```
ANALYSIS:   ESTIMATOR = BAYES;
            FBITER = 10000;
MODEL:      [y$1*.5] (mbeta0);
            y ON x*.3 (beta2);
            y ON m*.7 (beta1);
            y ON xm*.2 (beta3);
            [m*.5] (gamma0);
            m ON x*.5 (gamma1);
            m*.75 (sig2);
MODEL CONSTRAINT:
            NEW(ind*.45 dir*.4 arg11*.7 arg10*.25 arg01*.2 arg00*-
            .15 v1*1.6075 v0*1.3675 probit11*.5521 probit10*.1972
            probit01*.17103 probit00*-.1283 tie*.131 de*.129 pie*.119
            ortie*1.7788 orde*1.6808 orpie*1.614);
            dir=beta3*gamma0+beta2;
            ind=beta1*gamma1+beta3*gamma1;
            arg11=-mbeta0+beta2+(beta1+beta3)*(gamma0+gamma1);
            arg10=-mbeta0+beta2+(beta1+beta3)*gamma0;
            arg01=-mbeta0+beta1*(gamma0+gamma1);
            arg00=-mbeta0+beta1*gamma0;
            v1=(beta1+beta3)∧2*sig2+1;
            v0=beta1∧2*sig2+1;
            probit11=arg11/sqrt(v1);
            probit10=arg10/sqrt(v1);
            probit01=arg01/sqrt(v0);
            probit00=arg00/sqrt(v0);
            ! Phi function needed below:
            tie=phi(probit11)-phi(probit10);
            de=phi(probit10)-phi(probit00);
            pie=phi(probit01)-phi(probit00);
            ortie=(phi(probit11)/(1-phi(probit11)))/
            (phi(probit10)/(1-phi(probit10)));
            orde=(phi(probit10)/(1-phi(probit10)))/
            (phi(probit00)/(1-phi(probit00)));
            orpie=(phi(probit01)/(1-phi(probit01)))/
            (phi(probit00)/(1-phi(probit00)));
```

Table 30: Input for 1st rep step 2 bayes y on xm n=200

```
TITLE:    1st rep Binary Y, continuous M
DATA:     FILE = 1stn200.dat;
VARIABLE:
          NAMES = y m x;
          USEVARIABLES = y m x xm;
          CATEGORICAL = y;
DEFINE:   xm = x*m;
ANALYSIS:
          ESTIMATOR = BAYES;
          FBITER = 10000;
MODEL:
          [y$1*.5] (mbeta0);
          y ON x*.3 (beta2);
          y ON m*.7 (beta1);
          y ON xm*.2 (beta3);
          [m*.5] (gamma0);
          m ON x*.5 (gamma1);
          m*.75 (sig2);
MODEL CONSTRAINT:
          NEW(ind*.45 dir*.4 arg11*.7 arg10*.25 arg01*.2 arg00*-.15
          v1*1.6075 v0*1.3675 probit11*.5521 probit10*.1972 probit01*.17103
          probit00*-.1283 tie*.131 de*.129 pie*.119 ortie orde orpie);
          dir=beta3*gamma0+beta2;
          ind=beta1*gamma1+beta3*gamma1;
          arg11=-mbeta0+beta2+(beta1+beta3)*(gamma0+gamma1);
          arg10=-mbeta0+beta2+(beta1+beta3)*gamma0;
          arg01=-mbeta0+beta1*(gamma0+gamma1);
          arg00=-mbeta0+beta1*gamma0;
          v1=(beta1+beta3)^2*sig2+1;
          v0=beta1^2*sig2+1;
          probit11=arg11/sqrt(v1);
          probit10=arg10/sqrt(v1);
          probit01=arg01/sqrt(v0);
          probit00=arg00/sqrt(v0);
          ! Phi function needed below:
          tie=phi(probit11)-phi(probit10);
          de=phi(probit10)-phi(probit00);
          pie=phi(probit01)-phi(probit00);
          ortie=(phi(probit11)/(1-phi(probit11)))/
          (phi(probit10)/(1-phi(probit10)));
          orde=(phi(probit10)/(1-phi(probit10)))/
          (phi(probit00)/(1-phi(probit00)));
          orpie=(phi(probit01)/(1-phi(probit01)))/
          (phi(probit00)/(1-phi(probit00)));
OUTPUT: TECH1 TECH8;
PLOT:     TYPE = PLOT3;
```

Table 31: Input excerpts for juvcrt on agg5 on tx agg1 tx-agg5 probit

	USEVARIABLES = juvcrt agg5 agg1 tx xm;
	IDVARIABLE = prcid;
	CATEGORIAL = juvcrt;
	USEOBSERVATION = gender EQ 1 AND (desgn11s EQ 1 OR desgn11s EQ 2 OR desgn11s EQ 3 OR desgn11s EQ 4);
DEFINE:	IF(desgn11s EQ 4)THEN tx=1;
	IF(desgn11s EQ 1 OR desgn11s EQ 2 OR desgn11s EQ 3)THEN tx=0;
	agg1 = (sctaa11f-2.092)/1.0644;
	agg5 = (sctaa15s-2.400)/1.100;
	juvcrt = juvadl;
	xm = tx*agg5;
ANALYSIS:	ESTIMATOR = MLR;
	LINK = PROBIT;
	INTEGRATION = MONTECARLO;
MODEL:	[juvcrt$1] (mbeta0);
	juvcrt ON tx (beta2)
	agg5 (beta1)
	xm (beta3)
	agg1 (beta4);
	[agg5] (gamma0);
	agg5 ON tx (gamma1)
	agg1 (gamma2);
	agg5 (sig2);

Table 32: Input for juvcrt on agg5 on tx agg1 tx-agg5 probit, continued

MODEL CONSTRAINT:	NEW(ind dir arg11 arg10 arg00 v1 v0 probit11 probit10 probit00 indirect direct orind ordir);
	dir=beta3*gamma0+beta2;
	ind=beta1*gamma1+beta3*gamma1;
	arg11=-mbeta0+beta2+beta4*0+(beta1+beta3)*(gamma0+ gamma1+gamma2*0);
	arg10=-mbeta0+beta2+(beta1+beta3)*gamma0;
	arg00=-mbeta0+beta1*gamma0;
	v1=(beta1+beta3)∧2*sig2+1;
	v0=beta1∧2*sig2+1;
	probit11=arg11/sqrt(v1);
	probit10=arg10/sqrt(v1);
	probit00=arg00/sqrt(v0);
	! Phi function needed below:
	indirect=phi(probit11)-phi(probit10);
	direct=phi(probit10)-phi(probit00);
	orind=(phi(probit11)/(1-phi(probit11)))/(phi(probit10)/(1-phi(probit10)));
	ordir=(phi(probit10)/(1-phi(probit10)))/(phi(probit00)/(1-phi(probit00)));

OUTPUT:	TECH1 TECH8 SAMPSTAT PATTERNS STANDARDIZED;
PLOT:	TYPE = PLOT3;

Table 33: Input for juvcrt on agg5 on tx agg1 tx-agg5 logit

	USEVARIABLES = juvcrt agg5 agg1 tx xm;
	IDVARIABLE = prcid;
	CATEGORICAL = juvcrt;
	USEOBSERVATION = gender EQ 1 AND (desgn11s EQ 1 OR desgn11s EQ 2 OR desgn11s EQ 3 OR desgn11s EQ 4);
DEFINE:	IF(desgn11s EQ 4)THEN tx=1;
	IF(desgn11s EQ 1 OR desgn11s EQ 2 OR desgn11s EQ 3)THEN tx=0;
	agg1 = (sctaa11f-2.092)/1.0644;
	agg5 = (sctaa15s-2.400)/1.100;
	juvcrt = juvadl;
	xm = tx*agg5;
ANALYSIS:	ESTIMATOR = MLR;
	LINK = LOGIT;
	INTEGRATION = MONTECARLO;
MODEL:	[juvcrt$1] (mbeta0);
	juvcrt ON tx (beta2)
	agg5 (beta1)
	xm (beta3)
	agg1 (beta4);
	[agg5] (gamma0);
	agg5 ON tx (gamma1)
	agg1 (gamma2);
	agg5 (sig2);
MODEL CONSTRAINT:	
	NEW(ind*.45 dir*.4 oddsrat*.7);
	dir=beta2+beta3*gamma0;
	ind=beta1*gamma1+beta3*gamma1;
	oddsrat=exp(ind);
OUTPUT:	TECH1 TECH8 SAMPSTAT PATTERNS STANDARDIZED;
PLOT:	TYPE = PLOT3;

Table 34: Input for m cont probit using maximum-likelihood

```
TITLE:     Clinical Trials data M (intent) treated as continuous
DATA:      FILE = 4cat m.dat;
VARIABLE:
           NAMES = intent tx ciguse w;
           USEVARIABLE = tx ciguse intent;
           CATEGORICAL = ciguse;
           FREQWEIGHT = w;
DEFINE:    intent = (intent-1.456)/0.8854;
ANALYSIS:
           ESTIMATOR = MLR;
           LINK = PROBIT;
MODEL:     [ciguse$1] (mbeta0);
           ciguse ON tx (beta2)
           intent (beta1)
           [intent] (gamma0);
           intent ON tx (gamma1);
           intent (sig2);
MODEL CONSTRAINT:
           NEW(ind dir arg11 arg10 arg00 v1 v0 probit11 probit10
           probit00 indirect direct orind ordir);
           dir=beta2;
           ind=beta1*gamma1;
           arg11=-mbeta0+beta2+beta1*(gamma0+gamma1);
           arg10=-mbeta0+beta2+beta1*gamma0;
           arg00=-mbeta0+beta1*gamma0;
           v1=beta1∧2*sig2+1;
           v0=beta1∧2*sig2+1;
           probit11=arg11/sqrt(v1);
           probit10=arg10/sqrt(v1);
           probit00=arg00/sqrt(v0);
           ! Phi function needed below:
           indirect=phi(probit11)-phi(probit10);
           direct=phi(probit10)-phi(probit00);
           orind=(phi(probit11)/(1-phi(probit11)))/(phi(probit10)/(1-
           phi(probit10)));
           ordir=(phi(probit10)/(1-phi(probit10)))/(phi(probit00)/(1-
           phi(probit00)));
OUTPUT:    TECH1 TECH8 SAMPSTAT PATTERNS STANDARD-
           IZED;
PLOT:      TYPE = PLOT3;
```

Table 35: Input for m* cont probit using weighted least-squares

```
TITLE:    Clinical Trials data using M* as mediator
DATA:     FILE = 4cat m.dat;
VARIABLE:
          NAMES = intent tx ciguse w;
          USEVARIABLE = tx ciguse intent;
          CATEGORICAL = ciguse intent;
          FREQWEIGHT = w;
ANALYSIS:
          ESTIMATOR = WLSMV;
MODEL:    [ciguse$1] (mbeta0);
          ciguse ON tx (beta2)
          intent (beta1)
          intent ON tx (gamma1);
MODEL CONSTRAINT:
          NEW(ind dir arg11 arg10 arg00 v1 v0 probit11 probit10
          probit00 indirect direct orind ordir);
          dir=beta2;
          ind=beta1*gamma1;
          arg11=-mbeta0+beta2+beta1*(0+gamma1); ! gamma0=0
          for m*
          arg10=-mbeta0+beta2+beta1*0;
          arg00=-mbeta0+beta1*0;
          v1=beta1∧2*1+1; !sigma=1 for m* residual variance
          v0=beta1∧2*1+1;
          probit11=arg11/sqrt(v1);
          probit10=arg10/sqrt(v1);
          probit00=arg00/sqrt(v0);
          ! Phi function needed below:
          indirect=phi(probit11)-phi(probit10);
          direct=phi(probit10)-phi(probit00);
          orind=(phi(probit11)/(1-phi(probit11)))/(phi(probit10)/(1-
          phi(probit10)));
          ordir=(phi(probit10)/(1-phi(probit10)))/(phi(probit00)/(1-
          phi(probit00)));
OUTPUT:   TECH1 TECH8 SAMPSTAT PATTERNS STANDARD-
          IZED;
PLOT:     TYPE = PLOT3;
```

Table 36: Input for step 1 binary m binary y logit with xm interaction pearl ex n=400 tie and pie

```
TITLE: Pearl (2011) artificial example, Prevention Science
        (Model Constraint notation below vs Pearl's: fm -> h, fy->g)
        Step 1: Generate and analyze the data using the same model
MONTECARLO:
        NAMES = y m x; ! x: tx/ctrl, m: mediator, y: outcome
        CATEGORICAL = y m;
        GENERATE = y(1 l) m(1 l); ! binary DVs, logit link
        CUTPOINTS = x(0); ! binary tx/ctrl dummy
        NOBSERVATION = 400;
        NREPS = 500;
        REPSAVE = ALL;
        SAVE = binbinlogitrep*.dat;
MODEL POPULATION:
        x@1; [x@0];
        [m$1*.4055]; ! P(m=1 | x=0)=0.40
        m ON x*1.5041; ! P(m=1 | x=1)=0.75
        [y$1*1.3863]; ! P(y=1 | x=0, m=0)=0.20.
        y ON x*.9808; ! direct effect of x ON y. P(y=1 | x=1,m=0)=0.40
        beta1 | y ON m; ! defining the random slope
        [beta1*.539]; ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
        beta1 ON x*1.2528; ! interaction between x and m in their influence ON y.
        ! P(y=1 | x=1, m=1)=0.80
        beta1@0;
ANALYSIS:
        TYPE = RANDOM;
        ESTIMATOR = ML;
        LINK = LOGIT;
MODEL:
        [m$1*.4055] (Th0); ! Threshold=-Logit. P(m=1 | x=0)=0.40
        m ON x*1.5041 (Lh1); ! P(m=1 | x=1)=0.75
        [y$1*1.3863] (Tg00); ! Threshold=-Logit. P(y=1 | x=0,m=0)=0.20
        y ON x*.9808 (Lg10); ! direct effect of x ON y. P(y=1 | x=1,m=0)=0.40
        beta1 | y ON m; ! defining the random slope
        [beta1*.539]; ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
        beta1 ON x*1.2528; ! interaction between x and m in their influence ON y.
        ! P(y=1 | x=1, m=1)=0.80
        beta1@0;
```

Table 37: Input for step 1 binary m binary y logit with xm interaction pearl ex n=400 tie and pie, continued

```
MODEL CONSTRAINT:
        NEW(fm0*.4 fm1*.75 fy00*.2 fy10*.4 fy01*.3 fy11*.8
        de*.32 pie*.035 tie*.14 te*.46 iete*.07 dete*.696
        compdete*.304 tiete*.304);
        fm0=1/(1+exp(Th0));
        fm1=1/(1+exp(Th0-Lh1));
        fy00=1/(1+exp(Tg00));
        fy10=1/(1+exp(Tg00-Lg10));
        fy01=1/(1+exp(Tg00-Lg01));
        fy11=1/(1+exp(Tg00-Lg10-Lg01-Lg11));
        de=(fy10-fy00)*(1-fm0)+(fy11-fy01)*fm0;
        tie=(fy11-fy10)*(fm1-fm0);
        pie=(fy01-fy00)*(fm1-fm0);
        te=fy11*fm1+fy10*(1-fm1)-(fy01*fm0+fy00*(1-fm0));
        iete=pie/te;
        dete=de/te;
        compdete=1-de/te;
        tiete=tie/te;
```

Table 38: Input for step 2 define xm binary m binary y logit with xm interaction pearl ex n=400 tie and pie

```
TITLE: Pearl (2011) artificial example, Prevention Science (Model Constraint
       notation below vs Pearl's: fm -> h, fy->g)
       Step 2: Analyze the data using an interaction variable
DATA:
       FILE = binbinlogitreplist.dat;
       TYPE = MONTECARLO;
VARIABLE:
       NAMES = y m x; ! x: tx/ctrl, m: mediator, y: outcome
       CATEGORICAL = y m;
       USEVARIABLES = y m x xm;
DEFINE:
       xm = x*m; ! create the interaction variable
ANALYSIS:
       ESTIMATOR = ML;
       LINK = LOGIT;
MODEL:
       [m$1*.4055] (Th0); ! Threshold=-Logit. P(m=1 | x=0)=0.40
       m ON x*1.5041 (Lh1); ! P(m=1 | x=1)=0.75
       [y$1*1.3863] (Tg00); ! Threshold=-Logit. P(y=1 | x=0,m=0)=0.20
       y ON x*.9808 (Lg10); ! direct effect of x ON y. P(y=1 | x=1,m=0)=0.40
       y ON m*.539 (Lg01); ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
       y ON xm*1.2528 (Lg11); ! interaction between x and m
       ! in their influence ON y. P(y=1 | x=1,m=1)=0.80
MODEL CONSTRAINT:
       NEW(fm0*.4 fm1*.75 fy00*.2 fy10*.4 fy01*.3 fy11*.8
       de*.32 pie*.035 tie*.14 te*.46 iete*.07 dete*.696
       compdete*.304 tiete*.304);
       fm0=1/(1+exp(Th0));
       fm1=1/(1+exp(Th0-Lh1));
       fy00=1/(1+exp(Tg00));
       fy10=1/(1+exp(Tg00-Lg10));
       fy01=1/(1+exp(Tg00-Lg01));
       fy11=1/(1+exp(Tg00-Lg10-Lg01-Lg11));
       de=(fy10-fy00)*(1-fm0)+(fy11-fy01)*fm0;
       tie=(fy11-fy10)*(fm1-fm0);
       pie=(fy01-fy00)*(fm1-fm0);
       te=fy11*fm1+fy10*(1-fm1)-(fy01*fm0+fy00*(1-fm0));
       iete=pie/te;
       dete=de/te;
       compdete=1-de/te;
       tiete=tie/te;
```

Table 39: Input for step 1 binary m binary y probit with xm interaction pearl ex n=400

```
TITLE: Pearl (2011) artificial example, Prevention Science Probit link (Pearl-
       >Mplus notation: h->fm, g->fy)
MONTECARLO:
       NAMES = y m x; !x: tx/ctrl, m: mediator, y: outcome
       CATEGORICAL = y m;
       GENERATE = y(1 p) m(1 p); ! binary DVs, probit link
       CUTPOINTS = x(0); ! binary tx/ctrl dummy
       NOBSERVATION = 400;
       NREPS = 500;
       REPSAVE = ALL;
       SAVE = binbinprobrep*.dat;
MODEL POPULATION:
       x@1; [x@0];
       [m$1*.254]; ! P(m=1 | x=0)=0.40
       m ON x*.929; ! P(m=1 | x=1)=0.75
       [y$1*.84]; ! P(y=1 | x=0,m=0)=0.20
       y ON x*.586; ! direct effect of x ON y. P(y=1 |x=1,m=0)=0.40
       beta1 | y ON m;
       [beta1*.315]; ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
       beta1 ON x*.779; ! interaction between x AND m in their influence ON y
       !P(y=1 | x=1,m=1)=0.80
       beta1@0;
ANALYSIS:
       TYPE = RANDOM;
       ESTIMATOR = ML;
       LINK = PROBIT;
MODEL:
       [m$1*.254] (fm0); ! Negative intercept. P(m=1 | x=0)=0.40
       m ON x*.929 (fm1); ! P(m=1 | x=1)=0.75
       [y$1*.84] (fy00); ! Negative intercept. P(y=1 | x=0,m=0)=0.20
       y ON x*.586 (fy10); ! direct effect of x ON y. P(y=1 |x=1,m=0)=0.40
       beta1 | y ON m;
       [beta1*.315] (fy01); ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
       beta1 ON x*.779 (fy11); ! interaction between x AND m in their influence
       ON y
       !P(y=1 | x=1,m=1)=0.80
       beta1@0;
```

Table 40: Input for step 1 binary m binary y probit with xm interaction pearl ex n=400, continued

```
MODEL CONSTRAINT:
    NEW(de*.32 tie*.14 pie*.035 te*.46 tiete*.304 piete*.07 dete*.696
    compdete*.304 pfm0*.4 pfm1*.75 pfy00*.2 pfy10*.4 pfy01*.3 pfy11*.8);
    pfm0=phi(-fm0);
    pfm1=phi(-fm0+fm1);
    pfy00=phi(-fy00);
    pfy10=phi(-fy00+fy10);
    pfy01=phi(-fy00+fy01);
    pfy11=phi(-fy00+fy10+fy01+fy11);
    de=(pfy10-pfy00)*(1-pfm0)+(pfy11-pfy01)*pfm0;
    tie=(pfy11-pfy10)*(pfm1-pfm0);
    pie=(pfy01-pfy00)*(pfm1-pfm0);
    te=pfy11*pfm1+pfy10*(1-pfm1) -(pfy01*pfm0+pfy00*(1-pfm0));
    tiete=tie/te;
    piete=pie/te;
    dete=de/te;
    compdete=1-de/te;
```

Table 41: Input for step 2 ml define xm binary m binary y probit with xm interaction pearl ex n=400

```
TITLE: Pearl (2011) artificial example, Prevention Science Probit. Step 2
DATA:  FILE = binbinprobreplist.dat;
       TYPE = MONTECARLO;
VARIABLE:
       NAMES = y m x; !x: tx/ctrl, m: mediator, y: outcome
       CATEGORICAL = y m;
       USEVARIABLES = y m x xm;
DEFINE:
       xm = x*m;
ANALYSIS:
       ESTIMATOR = ML;
       LINK = PROBIT;
MODEL:
       [m$1*.254] (fm0); ! Negative intercept. P(m=1 | x=0)=0.40
       m on x*.929 (fm1); ! P(m=1 | x=1)=0.75
       [y$1*.84] (fy00); ! Negative intercept. P(y=1 | x=0,m=0)=0.20
       y ON x*.586 (fy10); ! direct effect of x ON y. P(y=1 | x=1,m=0)=0.40
       y ON m*.315 (fy01); ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
       y ON xm*.779 (fy11); ! interaction between x AND m in their influence
       ! ON y. P(y=1 | x=1,m=1)=0.80
MODEL CONSTRAINT:
       NEW(de*.32 tie*.14 pie*.035 te*.46 tiete*.304 piete*.07 dete*.696
       compdete*.304 pfm0*.4 pfm1*.75 pfy00*.2 pfy10*.4 pfy01*.3 pfy11*.8);
       pfm0=phi(-fm0);
       pfm1=phi(-fm0+fm1);
       pfy00=phi(-fy00);
       pfy10=phi(-fy00+fy10);
       pfy01=phi(-fy00+fy01);
       pfy11=phi(-fy00+fy10+fy01+fy11);
       de=(pfy10-pfy00)*(1-pfm0)+(pfy11-pfy01)*pfm0;
       tie=(fy11-pfy10)*(pfm1-pfm0);
       pie=(pfy01-pfy00)*(pfm1-pfm0);
       te=pfy11*pfm1+pfy10*(1-pfm1) - (pfy01*pfm0+pfy00*(1-pfm0));
       tiete=tie/te;
       piete=pie/te;
       dete=de/te;
       compdete=1-de/te;
```

Table 42: Input for step 2 bayes define xm binary m binary probit with xm interaction pearl ex n=400 10k

```
TITLE:
        Pearl (2011) artificial example, Prevention Science
        Step 2. Bayes analysis
DATA:
        FILE = binbinprobreplist.dat;
        TYPE = MONTECARLO;
VARIABLE:
        NAMES = y m x; !x: tx/ctrl, m: mediator, y: outcome
        CATEGORICAL = y m;
        USEVARIABLES = y m x xm;
DEFINE:
        xm = x*m;
ANALYSIS:
        ESTIMATOR = BAYES;
        FBITER = 10000;
        MEDIATOR = OBSERVED;
MODEL:
        [m$1*.254] (fm0); ! Negative intercept. P(m=1 | x=0)=0.40
        m ON x*.929 (fm1); ! P(m=1 | x=1)=0.75
        [y$1*.84] (fy00); ! Negative intercept. P(y=1 | x=0,m=0)=0.20
        y ON x*.586 (fy10); ! direct effect of x ON y. P(y=1 |x=1,m=0)=0.40
        y ON m*.315 (fy01); ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
        y ON xm*.779 (fy11); ! interaction between x and m in their
        ! influence ON y. P(y=1 | x=1,m=1)=0.80
```

Table 43: Input for step 2 bayes define xm binary m binary probit with xm interaction pearl ex n=400 10k, continued

```
MODEL CONSTRAINT:
    NEW(de*.32 tie*.14 pie*.035 te*.46 tiete*.304 piete*.07
    dete*.696 compdete*.304 orde*4.0303 ortie*1.8333 pfm0 pfm1
    pfy00 pfy10 pfy01 pfy11 numde dende numtie dentie);
    pfm0=phi(-fm0);
    pfm1=phi(-fm0+fm1);
    pfy00=phi(-fy00);
    pfy10=phi(-fy00+fy10);
    pfy01=phi(-fy00+fy01);
    pfy11=phi(-fy00+fy10+fy01+fy11);
    de=(pfy10-pfy00)*(1-pfm0)+(pfy11-pfy01)*pfm0;
    tie=(pfy11-pfy10)*(pfm1-pfm0);
    pie=(pfy01-pfy00)*(pfm1-pfm0);
    te=pfy11*pfm1+pfy10*(1-pfm1)-(pfy01*pfm0+pfy00*(1-
    pfm0));
    tiete=tie/te;
    piete=pie/te;
    dete=de/te;
    compdete=1-de/te;
    numde=pfy10*(1-pfm0)+pfy11*pfm0;
    dende=pfy00*(1-pfm0)+pfy01*pfm0;
    orde=(numde/(1-numde))/(dende/(1-dende));
    numtie=pfy10*(1-pfm1)+pfy11*pfm1;
    dentie=pfy10*(1-pfm0)+pfy11*pfm0;
    ortie=(numtie/(1-numtie))/(dentie/(1-dentie));
```

Table 44: Input for Bayes analysis of n=200 data drawn on the Pearl example

```
TITLE: Pearl (2011) artificial example for n=200 probit.
DATA:  FILE = n200.dat;
VARIABLE:
       NAMES = y m x w; ! x: tx/ctrl, m: mediator, y: outcome
       FREQWEIGHT = w;
       CATEGORICAL = y m;
       USEVARIABLES = y m x xm;
DEFINE:
       xm = x*m;
ANALYSIS:
       ESTIMATOR = BAYES;
       FBITER = 10000;
       MEDIATOR = OBSERVED;
MODEL:
       [m$1*.254] (fm0); ! Negative intercept. P(m=1 | x=0)=0.40
       m ON x*.929 (fm1); ! P(m=1 | x=1)=0.75
       [y$1*.84] (fy00); ! Negative intercept. P(y=1 | x=0,m=0)=0.20
       y ON x*.586 (fy10); ! direct effect of x ON y. P(y=1 | x=1,m=0)=0.40
       y ON m*.315 (fy01); ! main effect of m ON y. P(y=1 | x=0,m=1)=0.30
       y ON xm*.779 (fy11); ! interaction between x and m in their influence
       ! ON y P(y=1 | x=1,m=1)=0.80
```

Table 45: Input for Bayes analysis of n=200 data drawn on the Pearl example, continued

```
MODEL CONSTRAINT:
        NEW(de*.32 tie*.14 pie*.035 te*.46 tiete*.304 piete*.07
        dete*.696 compdete*.304 pfm0*.4 pfm1*.75 pfy00*.2 pfy10*.4
        pfy01*.3 pfy11*.8 numde*.56 dende*.24 orde*4.0303 numind*.7
        denind*.56 orind*1.8333);
        pfm0=phi(-fm0);
        pfm1=phi(-fm0+fm1);
        pfy00=phi(-fy00);
        pfy10=phi(-fy00+fy10);
        pfy01=phi(-fy00+fy01);
        pfy11=phi(-fy00+fy10+fy01+fy11);
        de=(pfy10-pfy00)*(1-pfm0)+(pfy11-pfy01)*pfm0;
        tie=(pfy11-pfy10)*(pfm1-pfm0);
        pie=(pfy01-pfy00)*(pfm1-pfm0);
        te=pfy11*pfm1+pfy10*(1-pfm1)-(pfy01*pfm0+pfy00*(1-
        pfm0));
        tiete=tie/te;
        piete=pie/te;
        dete=de/te;
        compdete=1-de/te;
        numde=pfy10*(1-pfm0)+pfy11*pfm0;
        dende=pfy00*(1-pfm0)+pfy01*pfm0;
        orde=(numde/(1-numde))/(dende/(1-dende));
        numind=pfy10*(1-pfm1)+pfy11*pfm1;
        denind=pfy10*(1-pfm0)+pfy11*pfm0;
        orind=(numind/(1-numind))/(denind/(1-denind));
OUTPUT:
        TECH1 TECH8;
PLOT:   TYPE = PLOT3;
```

Table 46: Input for step 1 y on xm n=800

```
TITLE:        Nominal M, Continuous Y
              Using a latent class variable to represent M
              Simulating x-m interaction effect ON y by class-varying y
              ON x
              Step 1: Saving the data for external Monte Carlo analysis
MONTECARLO:
              NAMES = y x;
              GENCLASSES = c(3);
              CLASSES = c(3);
              NOBSERVATION = 800;
              NREPS = 500;
              REPSAVE = ALL;
              SAVE = n800xmrep*.dat;
              CUTPOINTS = x(0);
MODEL POPULATION:
              %OVERALL%
              x@1;
              [c#1*-1];
              [c#2*-.5];
              c#1 ON x*.7;
              c#2 ON x*.3;
              y ON x*0;
              y*.75;
              %c#1%
              [y*-2];
              y ON x*-.5;
              %c#2%
              [y*0];
              y ON x*-.3;
              %c#3%
              [y*2];
              y ON x*-.2;
```

Table 47: Input for step 1 y on xm n=800, continued

ANALYSIS:	TYPE = MIXTURE;
	ESTIMATOR = ML;
MODEL:	%OVERALL%
	[c#1*-1];
	[c#2*-.5];
	c#1 ON x*.7;
	c#2 ON x*.3;
	y ON x*0;
	y*.75;
	%c#1%
	[y*-2];
	y ON x*-.5;
	%c#2%
	[y*0];
	y ON x*-.3;
	%c#3%
	[y*2];
	y ON x*-.2;

Table 48: Input for step 2 y on xm knownclass

TITLE:	Nominal M, Continuous Y Using a latent class variable to represent M Simulating x-m interaction effect ON y by class-varying y ON x Step 2: External Monte Carlo Analysis
DATA:	FILE = n800xmreplist.dat; TYPE = MONTECARLO;
VARIABLE:	NAMES = y x m; USEVARIABLES = y x; CLASSES = c(3); KNOWNCLASS = c(m=1 m=2 m=3);
ANALYSIS:	TYPE = MIXTURE; ESTIMATOR = ML;
MODEL:	%OVERALL% [c#1*-1] (gamma01); [c#2*-.5] (gamma02); c#1 ON x*.7 (gamma11); c#2 ON x*.3 (gamma12); y ON x*0; y*.75; %c#1% [y*-2] (beta01); y ON x*-.5 (beta11); %c#2% [y*0] (beta02); y ON x*-.3 (beta12); %c#3% [y*2] (beta03); y ON x*-.2 (beta13);

Table 49: Input for step 2 y on xm knownclass, continued

```
MODEL CONSTRAINT:
          NEW(denom0*1.9744 denom1*2.5595 p10*.1863
          p11*.2894 p20*.3072 p21*.3199 p30*.5065 p31*.3907
          term11*-.1162 term10*.3538 term01*.2026 term00*.6404
          de*-.2866 tie*-.47 total*-.7566 pie*-.4378);
          ! index is x' for multinomial denominator
          denom0=exp(gamma01)+exp(gamma02)+1;
          denom1=exp(gamma01+gamma11)+exp(gamma02+gamma12)+1;
          ! first index is class, second x' for probabilities
          p10=exp(gamma01)/denom0;
          p11=exp(gamma01+gamma11)/denom1;
          p20=exp(gamma02)/denom0;
          p21=exp(gamma02+gamma12)/denom1;
          p30=1/denom0;
          p31=1/denom1;
          ! first index is x, second x', summing over class
          term11=(beta01+beta11)*p11+(beta02+beta12)*p21
          +(beta03+beta13)*p31;
          term10=(beta01+beta11)*p10+(beta02+beta12)*p20
          +(beta03+beta13)*p30;
          term01=(beta01)*p11+(beta02)*p21+(beta03)*p31;
          term00=(beta01)*p10+(beta02)*p20+(beta03)*p30;
          de=term10-term00;
          tie=term11-term10;
          total=term11-term00;
          pie=term01-term00;
```

Table 50: Input for hypothetical pollution data with a nominal mediator and a binary outcome

TITLE:	Nominal M, Binary Y
	Using a latent class variable to represent M
DATA:	FILE = nombin.dat;
VARIABLE:	NAMES = x m y w;
	FREQWEIGHT = w;
	USEVARIABLES = y x;
	CATEGORICAL = y;
	CLASSES = c(3);
	KNOWNCLASS = c(m=1 m=2 m=3);
ANALYSIS:	TYPE = MIXTURE;
	ESTIMATOR = ML;
MODEL:	%OVERALL%
	[c#1] (gamma01);
	[c#2] (gamma02);
	c#1 ON x (gamma11);
	c#2 ON x (gamma12);
	y ON x;
	%c#1%
	[y$1] (beta01);
	y ON x (beta11);
	%c#2%
	[y$1] (beta02);
	y ON x (beta12);
	%c#3%
	[y$1] (beta03);
	y ON x (beta13);

Table 51: Input for hypothetical pollution data with a nominal mediator and a binary outcome, continued

```
MODEL CONSTRAINT:
          NEW(denom0 denom1 p10 p11 p20 p21 p30 p31 term11
          term10 term01 term00 de tie total pie orde ortie orpie);
          ! index is x' for multinomial denominator
          denom0=exp(gamma01)+exp(gamma02)+1;
          denom1=exp(gamma01+gamma11)+exp(gamma02+gamma12)+1;
          ! first index is class, second x' for probabilities
          p10=exp(gamma01)/denom0;
          p11=exp(gamma01+gamma11)/denom1;
          p20=exp(gamma02)/denom0;
          p21=exp(gamma02+gamma12)/denom1;
          p30=1/denom0;
          p31=1/denom1;
          ! first index is x, second x', summing over class
          term11=(1/(1+exp(beta01-beta11)))*p11+(1/(1+exp(beta02-
          beta12)))*p21 +(1/(1+exp(beta03-beta13)))*p31;
          term10=(1/(1+exp(beta01-beta11)))*p10+(1/(1+exp(beta02-
          beta12)))*p20 +(1/(1+exp(beta03-beta13)))*p30;
          term01=(1/(1+exp(beta01)))*p11+(1/(1+exp(beta02)))*p21
          +(1/(1+exp(beta03)))*p31;
          term00=(1/(1+exp(beta01)))*p10+(1/(1+exp(beta02)))*p20
          +(1/(1+exp(beta03)))*p30;
          de=term10-term00;
          tie=term11-term10;
          total=term11-term00;
          pie=term01-term00;
          orde=(term10/(1-term10))/(term00/(1-term00));
          ortie=(term11/(1-term11))/(term10/(1-term10));
          orpie=(term01/(1-term01))/(term00/(1-term00));
OUTPUT:   TECH1 TECH8;
```

Table 52: Input for step 1 count y on xm

```
TITLE:        Simulating x-m interaction effect on y using a random slope
              Count Y, continuous M
              Step 1: saving the data for external Monte Carlo analysis
MONTECARLO:
              NAMES = y m x;
              GENERATE = y(p);
              COUNT = y(p);
              NOBSERVATION = 400;
              NREPS = 500;
              REPSAVE = ALL;
              SAVE = xmrep*.dat;
              CUTPOINTS = x(0);
MODEL POPULATION:
              x@1;
              [y*-.7]; ! this log rate gives a rate of about 0.5
              y ON x*.3;
              beta1 | y ON m;
              beta1 ON x*.2;
              [beta1*.4];
              beta1@0;
              [m*.5];
              m ON x*.5;
              m*.75;
ANALYSIS:     TYPE = RANDOM;
              ESTIMATOR = ML;
MODEL:        [y*-.7] (beta0);
              y ON x*.3 (beta2);
              beta1 | y ON m;
              beta1 ON x*.2 (beta3);
              [beta1*.4] (beta1);
              beta1@0;
              [m*.5] (gamma0);
              m ON x*.5 (gamma1);
              m*.75 (sig);
```

Table 53: Input for step 1 count y on xm, continued

```
MODEL CONSTRAINT:
          NEW(ind*.45 dir*.4 ey1 ey0 mum1 mum0 ay1 ay0 bym11
          bym10 bym01 bym00 eym11 eym10 eym01 eym00 tie de
          total pie);
          ind=beta1*gamma1+beta3*gamma1;
          dir=beta3*gamma0+beta2;
          ey1=exp(beta0+beta2);
          ey0=exp(beta0);
          mum1=gamma0+gamma1;
          mum0=gamma0;
          ay1=2*sig*(beta1+beta3);
          ay0=2*sig*beta1;
          bym11=(ay1/mum1+2)/2;
          bym10=(ay1/mum0+2)/2;
          bym01=(ay0/mum1+2)/2;
          bym00=(ay0/mum0+2)/2;
          eym11=exp((bym11*bym11-1)*mum1*mum1/(2*sig));
          eym10=exp((bym10*bym10-1)*mum0*mum0/(2*sig));
          eym01=exp((bym01*bym01-1)*mum1*mum1/(2*sig));
          eym00=exp((bym00*bym00-1)*mum0*mum0/(2*sig));
          tie=ey1*eym11-ey1*eym10;
          de=ey1*eym10-ey0*eym00;
          total=ey1*eym11-ey0*eym00;
          pie=ey0*eym01-ey0*eym00;
```

Table 54: Input for step 2 count y on xm

```
TITLE:      Simulating x-m interaction effect on y using a random slope
            Binary Y, continuous M
            Step 2: External Monte Carlo analysis
DATA:       FILE = xmreplist.dat;
            TYPE = MONTECARLO;
VARIABLE:   NAMES = y m x;
            USEVARIABLES = y m x xm;
            COUNT = y(p);
DEFINE:     xm = x*m;
ANALYSIS:   ESTIMATOR = ML;
MODEL:      [y*-.7] (beta0);
            y ON x*.3 (beta2);
            y ON m*.4 (beta1);
            y ON xm*.2 (beta3);
            [m*.5] (gamma0);
            m on x*.5 (gamma1);
            m*.75 (sig);
MODEL CONSTRAINT:
            NEW(ind*.45 dir*.4 ey1*.67032 ey0*.49658 mum1*1
            mum0*.5 ay1*.9 ay0*.6 bym11*1.45 bym10*1.9 bym01*1.3
            bym00*1.6 eym11*2.0855 eym10*1.5450 eym01*1.5841
            eym00*1.2969 tie*.3361 de*.3916 total*.7539 pie*.1426);
            ind=beta1*gamma1+beta3*gamma1;
            dir=beta3*gamma0+beta2;
            ey1=exp(beta0+beta2);
            ey0=exp(beta0);
            mum1=gamma0+gamma1;
            mum0=gamma0;
            ay1=2*sig*(beta1+beta3);
            ay0=2*sig*beta1;
            bym11=(ay1/mum1+2)/2;
            bym10=(ay1/mum0+2)/2;
            bym01=(ay0/mum1+2)/2;
            bym00=(ay0/mum0+2)/2;
            eym11=exp((bym11*bym11-1)*mum1*mum1/(2*sig));
            eym10=exp((bym10*bym10-1)*mum0*mum0/(2*sig));
            eym01=exp((bym01*bym01-1)*mum1*mum1/(2*sig));
            eym00=exp((bym00*bym00-1)*mum0*mum0/(2*sig));
            tie=ey1*eym11-ey1*eym10;
            de=ey1*eym10-ey0*eym00;
            total=ey1*eym11-ey0*eym00;
            pie=ey0*eym01-ey0*eym00;
```

Table 55: Input for rho=0 run: replicating regular mediation analysis

```
TITLE:       Generate as M on X, Y on M and X
             Analyze as M on X, Y on X
             Using Imai formulas with rho=0,
             so same as regular mediation run
MONTECARLO:
             NAMES = y m x;
             NOBSERVATION = 400;
             NREPS= 500;
             CUTPOINTS = x(0);
MODEL POPULATION:
             x@1;
             [y*1]; ! beta0
             y ON m*.5 ! beta1
             x*.4; ! beta2
             [m*2]; ! gamma0
             m ON x*.5; ! gamma1
             y*.5; ! sig1
             m*1; ! sig2
ANALYSIS:
MODEL:       [y] (kappa0);
             y ON x (kappa1);
             [m*2] (gamma0);
             m ON x*.5 (gamma1);
             y*.75 (sig);
             m*1 (sig2);
             y WITH m*.5 (cov);
MODEL CONSTRAINT:
             NEW(rhocurl*.5774 beta1*.5 beta2*.4 beta0*1 sig1*.5
             ind*.25 de*.4);
             rhocurl=cov/(sqrt(sig)*sqrt(sig2));
             ! derive the data-generating model parameters
             ! from the analysis model parameters:
             beta1=rhocurl*sqrt(sig)/sqrt(sig2);
             beta2=kappa1-beta1*gamma1;
             beta0=kappa0-beta1*gamma0;
             sig1=sig-beta1*beta1*sig2;
             ! express the effects in terms of the data-generating
             ! parameters:
             ind=beta1*gamma1;
             de=beta2;
```

Table 56: Input for true corr=0.25, rho=0.25

```
TITLE:        Generate as M on X, Y on M and X
              adding a residual correlation of rho=0.25
              Analyze as M on X, Y on X
              Using Imai formulas for sensitivity analysis
MONTECARLO:
              NAMES = y m x;
              NOBSERVATION = 400;
              NREPS = 500;
              CUTPOINTS = x(0);
MODEL POPULATION:
              x@1;
              [y*1]; ! beta0
              y ON m*.5 ! beta1
              x*.4; ! beta2
              [m*2]; ! gamma0
              m ON x*.5; ! gamma1
              y*.5; ! sig1
              m*1; ! sig2
              y WITH m*.1768; ! gives res corr 0.25
ANALYSIS:
MODEL:        [y] (kappa0);
              y ON x (kappa1);
              [m*2] (gamma0);
              m ON x*.5 (gamma1);
              y*1.1036 (sig);
              m*1 (sig2);
              y WITH m*.8536 (cov);
MODEL CONSTRAINT:
              NEW(rho*.25 rhocurl*.8125 beta1*.5 beta2*.4 beta0*1
              sig1*.7071 ind*.25 de*.4);
              rhocurl=cov/(sqrt(sig)*sqrt(sig2));
              rho=.25;
              beta1=(sqrt(sig)/sqrt(sig2))*
              (rhocurl-rho*sqrt((1-rhocurl*rhocurl)/(1-rho*rho)));
              beta2=kappa1-beta1*gamma1;
              beta0=kappa0-beta1*gamma0;
              sig1=(rhocurl*sqrt(sig)-beta1*sqrt(sig2))/0.5;
              ind=beta1*gamma1;
              de=beta2;
```

Table 57: Input excerpts for head circumference analysis with rho=0 corresponding to regular mediation analysis

```
MODEL:      [hcirc36] (kappa0);
            hcirc36 ON alccig (kappa1)
            gender eth;
            [hcirc0] (gamma0);
            hcirc0 ON alccig*1 (gamma1)
            gender eth;
            hcirc36*1 (sig);
            hcirc0*1 (sig2);
            hcirc36 WITH hcirc0 (cov);
MODEL CONSTRAINT:
            NEW(rho rhocurl beta1 beta2 beta0 sig1 indirect direct);
            rhocurl=cov/(sqrt(sig)*sqrt(sig2));
            rho=0;
            beta1=(sqrt(sig)/sqrt(sig2))*
            (rhocurl-rho*sqrt((1-rhocurl*rhocurl)/(1-rho*rho)));
            beta2=kappa1-beta1*gamma1;
            beta0=kappa0-beta1*gamma0;
            sig1=(rhocurl*sqrt(sig)-beta1*sqrt(sig2))/0.5;
            indirect=beta1*gamma1;
            direct=beta2;
OUTPUT:     SAMPSTAT STANDARDIZED;
PLOT:       TYPE = PLOT3;
```