



User: Zara Izadi
Project: EPI III

```
> under a causal structure consistent with this hypothesized causal structure.
  name: <unnamed>
  log: C:\Users\z_iza\Desktop\PhD\Classes\Epi III\Session 7\mediation.smcl
  log type: smcl
  opened on: 21 May 2019, 16:02:15
```

```
1 .
2 . *****Zara Izadi*****
3 .
4 . /*
5 . > Specify a hypothesis regarding a binary exposure, a continuous mediator,
6 . > and a continuous outcome. Specify how each variable affects its children
7 . > i.e., how the exposure influences the mediator) and the distribution of the
8 . > random or unmeasured determinants of the child variables.
9 . > */
10 .
11 . * Direct effect of x on y, not mediated by m is 1.3
12 . * Indirect effect of x on y, via m is 1.6 (2*0.8)
13 . * Total effect of x on y is 1.3+1.6=2.9 and there is no interaction between m and x
14 .
15 . /*Using the software of your choice, generate a population with 10000 people
16 . > under a causal structure consistent with this hypothesized causal structure.
17 . > */
18 .
19 . clear
20 .
21 . set seed 4321
22 .
23 . set obs 100000
24 . number of observations (_N) was 0, now 100,000
25 .
26 . gen x=runiform()<.5
27 .
28 . gen m=2*x+rnormal()*1.5
29 .
30 . gen y=1.3*x+0.8*m+rnormal()
31 .
32 .
33 . /*Use a conventional Baron-Kenny decomposition to estimate the direct and indirect
34 . > effects of the exposure on the outcome.
35 . > */
36 .
37 . reg y x
```

Source	SS	df	MS	Number of obs	=	100,000
Model	212553.188	1	212553.188	F(1, 99998)	=	87332.65
Residual	243378.547	99,998	2.43383415	Prob > F	=	0.0000
Total	455931.735	99,999	4.55936294	R-squared	=	0.4662
				Adj R-squared	=	0.4662
				Root MSE	=	1.5601

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	2.915892	.009867	295.52	0.000	2.896553	2.935231
_cons	-.0104899	.0069562	-1.51	0.132	-.0241241	.0031442

```
22 . scalar total_effect=_b[x]
```

```
23 . reg y x m
```

Source	SS	df	MS	Number of obs	=	100,000
Model	355942.712	2	177971.356	F(2, 99997)	>	99999.00
Residual	99989.0232	99,997	.99992023	Prob > F	=	0.0000
				R-squared	=	0.7807
				Adj R-squared	=	0.7807
Total	455931.735	99,999	4.55936294	Root MSE	=	.99996

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	1.304514	.0076227	171.14	0.000	1.289574	1.319455
m	.8003288	.0021135	378.68	0.000	.7961864	.8044711
_cons	-.0025224	.0044588	-0.57	0.572	-.0112616	.0062168

```
24 . scalar direct_effect=_b[x]
```

```
25 . dis in red "indirect effect is: " round(total_effect-direct_effect,.001)
indirect effect is: 1.611
```

```
26 .
27 . /*Now introduce a confounder of the mediator and outcome (C) into your causal
> model. Define the new causal models and simulate a new data set.
> Use a conventional decomposition without control for the confounder first and
> then with control for the confounder to derive estimates of the direct and
> indirect effects of exposure on outcome.
> */
```

```
28 .
29 . clear
```

```
30 . set seed 4321
```

```
31 . set obs 100000
number of observations (_N) was 0, now 100,000
```

```
32 . gen x=runiform()<.5
```

```
33 . gen c=rnormal()
```

```
34 . gen m=2*x+c+rnormal()*1.5
```

```
35 . gen y=1.3*x+0.8*m+0.5*c+rnormal()
```

```
36 .
37 . * Using BK:
38 . reg y x
```

Source	SS	df	MS	Number of obs	=	100,000
Model	212715.089	1	212715.089	F(1, 99998)	=	51940.34
Residual	409529.15	99,998	4.09537341	Prob > F	=	0.0000
				R-squared	=	0.3419
				Adj R-squared	=	0.3418
Total	622244.239	99,999	6.22250461	Root MSE	=	2.0237

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	2.917003	.0127992	227.90	0.000	2.891916	2.942089
_cons	-.0133455	.0090235	-1.48	0.139	-.0310314	.0043405

39 . scalar total_effect_est=_b[x]

40 . reg y m

Source	SS	df	MS	Number of obs	=	100,000
Model	486946.11	1	486946.11	F(1, 99998)	>	99999.00
Residual	135298.129	99,998	1.35300835	Prob > F	=	0.0000
				R-squared	=	0.7826
				Adj R-squared	=	0.7826
Total	622244.239	99,999	6.22250461	Root MSE	=	1.1632

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
m	1.068779	.0017815	599.92	0.000	1.065288	1.072271
_cons	.3763356	.0040808	92.22	0.000	.3683373	.384334

41 . reg y m x

Source	SS	df	MS	Number of obs	=	100,000
Model	505988.162	2	252994.081	F(2, 99997)	>	99999.00
Residual	116256.077	99,997	1.16259565	Prob > F	=	0.0000
				R-squared	=	0.8132
				Adj R-squared	=	0.8132
Total	622244.239	99,999	6.22250461	Root MSE	=	1.0782

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
m	.9504966	.0018925	502.25	0.000	.9467874	.9542059
x	1.000141	.0078148	127.98	0.000	.9848244	1.015458
_cons	-.0034362	.0048078	-0.71	0.475	-.0128594	.0059871

42 . scalar biased_direct_effect_est=_b[x]

43 .

44 . * Checking that right answer is obtained with controlling for C:

45 . reg y m x c

Source	SS	df	MS	Number of obs	=	100,000
Model	523064.792	3	174354.931	F(3, 99996)	>	99999.00
Residual	99179.447	99,996	.991834144	Prob > F	=	0.0000
				R-squared	=	0.8406
				Adj R-squared	=	0.8406
Total	622244.239	99,999	6.22250461	Root MSE	=	.99591

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
m	.7978567	.0020997	379.99	0.000	.7937413	.801972
x	1.303526	.0075794	171.98	0.000	1.28867	1.318381
c	.4976456	.0037926	131.21	0.000	.4902121	.505079
_cons	-.0017247	.0044407	-0.39	0.698	-.0104285	.0069791

```

46 . scalar direct_effect_est=_b[x]
47 . dis direct_effect_est
1.3035256
48 . dis in red "indirect effect estimated w/o control for c is: " round(total_effect_est-biased_dir
indirect effect estimated w/o control for c is: 1.917
49 . dis in red "indirect effect estimated w/ control for c is: " round(total_effect_est-direct_eff
indirect effect estimated w/ control for c is: 1.613
50 . dis in red "total effect is: " round(total_effect_est,.001)
total effect is: 2.917
51 .
52 . ** Checking it w/ paramed
53 .
54 . paramed y ,avar(x) mvar(m) a0(0) a1(1) m(0) yreg(linear) mreg(linear) cvars(c)

```

Source	SS	df	MS	Number of obs	=	100,000
Model	523065.141	4	130766.285	F(4, 99995)	>	99999.00
Residual	99179.098	99,995	.991840572	Prob > F	=	0.0000
				R-squared	=	0.8406
				Adj R-squared	=	0.8406
Total	622244.239	99,999	6.22250461	Root MSE	=	.99591

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	1.305609	.0083532	156.30	0.000	1.289236	1.321981
m	.798887	.0027249	293.18	0.000	.7935462	.8042277
_x_X_m	-.002074	.0034961	-0.59	0.553	-.0089262	.0047783
_c	.4976642	.0037928	131.21	0.000	.4902305	.505098
_cons	-.0017138	.0044408	-0.39	0.700	-.0104177	.00699

Source	SS	df	MS	Number of obs	=	100,000
Model	201314.322	2	100657.161	F(2, 99997)	=	44740.08
Residual	224975.302	99,997	2.24982052	Prob > F	=	0.0000
				R-squared	=	0.4722
				Adj R-squared	=	0.4722
Total	426289.624	99,999	4.26293887	Root MSE	=	1.4999

m	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	2.007758	.0094867	211.64	0.000	1.989164	2.026351
c	1.00074	.0047553	210.45	0.000	.9914194	1.01006
_cons	-.0037836	.0066882	-0.57	0.572	-.0168923	.0093251

	Estimate	Std Err	P> z	[95% Conf Interval]	
cde	1.3056085	.00835323	0.000	1.2892362	1.3219809
nde	1.3056209	.00836205	0.000	1.2892313	1.3220106
nie	1.5998073	.00934822	0.000	1.5814848	1.6181298
mte	2.9054283	.00984705	0.000	2.886128	2.9247285

cde:controlled direct effect, nde:natural direct effect, nie:natural indirect effect, mte:marginal

```

55 .
56 . /*Create a new version of the mediator that represents a badly measured version
> of that variable, for example by taking the original variable and adding some
> random noise to it. Now use that mediator to evaluate the direct and indirect
> effects.
> */

```

```

57 . gen m_measured=m+rnormal()*0.7

```

```

58 . sum

```

Variable	Obs	Mean	Std. Dev.	Min	Max
x	100,000	.49703	.4999937	0	1
c	100,000	-.0021984	.9974831	-4.219059	4.520502
m	100,000	.9919322	2.064689	-7.076925	9.336992
y	100,000	1.436492	2.494495	-8.168898	11.40392
m_measured	100,000	.9904762	2.180661	-7.691277	9.988099

```

59 .
60 . * Redo above
61 . * Use BK
62 . reg y x

```

Source	SS	df	MS	Number of obs	=	100,000
Model	212715.089	1	212715.089	F(1, 99998)	=	51940.34
Residual	409529.15	99,998	4.09537341	Prob > F	=	0.0000
				R-squared	=	0.3419
				Adj R-squared	=	0.3418
Total	622244.239	99,999	6.22250461	Root MSE	=	2.0237

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x	2.917003	.0127992	227.90	0.000	2.891916 2.942089
_cons	-.0133455	.0090235	-1.48	0.139	-.0310314 .0043405

```

63 . scalar total_effect_werror=_b[x]

```

```

64 . reg y m_measured

```

Source	SS	df	MS	Number of obs	=	100,000
Model	436296.522	1	436296.522	F(1, 99998)	>	99999.00
Residual	185947.717	99,998	1.85951436	Prob > F	=	0.0000
				R-squared	=	0.7012
				Adj R-squared	=	0.7012
Total	622244.239	99,999	6.22250461	Root MSE	=	1.3636

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
m_measured	.9578664	.0019775	484.39	0.000	.9539905 .9617422
_cons	.4877485	.0047362	102.98	0.000	.4784656 .4970313

65 . reg y m_measured x

Source	SS	df	MS	Number of obs	=	100,000
Model	467045.52	2	233522.76	F(2, 99997)	>	99999.00
Residual	155198.719	99,997	1.55203375	Prob > F	=	0.0000
				R-squared	=	0.7506
				Adj R-squared	=	0.7506
Total	622244.239	99,999	6.22250461	Root MSE	=	1.2458

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
m_measured	.8250606	.0020382	404.81	0.000	.8210658	.8290554
x	1.251197	.0088892	140.76	0.000	1.233775	1.26862
_cons	-.0025931	.005555	-0.47	0.641	-.0134809	.0082946

66 . scalar biased_direct_effect_werror=_b[x]

67 . reg y m_measured x c

Source	SS	df	MS	Number of obs	=	100,000
Model	497213.118	3	165737.706	F(3, 99996)	>	99999.00
Residual	125031.12	99,996	1.25036122	Prob > F	=	0.0000
				R-squared	=	0.7991
				Adj R-squared	=	0.7991
Total	622244.239	99,999	6.22250461	Root MSE	=	1.1182

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
m_measured	.6540932	.002135	306.37	0.000	.6499086	.6582777
x	1.590643	.0082725	192.28	0.000	1.574429	1.606857
c	.6426292	.0041372	155.33	0.000	.6345203	.6507381
_cons	-.0005562	.004986	-0.11	0.911	-.0103287	.0092164

68 . scalar direct_effect_est_werror=_b[x]

69 . dis in red "biased direct effect estimated w/o control for c is: " round(biased_direct_effect_werror, 0.001)
biased direct effect estimated w/o control for c is: 1.251

70 . dis in red "direct effect estimated w control for c is: " round(direct_effect_est_werror, 0.001)
direct effect estimated w control for c is: 1.591

71 . dis in red "indirect effect estimated w/o control for c is: " round(total_effect_werror-biased_direct_effect_est_werror, 0.001)
indirect effect estimated w/o control for c is: 1.666

72 . dis in red "indirect effect estimated w/ control for c is: " round(total_effect_werror-direct_effect_est_werror, 0.001)
indirect effect estimated w/ control for c is: 1.326

73 . dis in red "total effect is: " round(total_effect_werror, .001)
total effect is: 2.917

```

74 .
75 . /*Now try estimating the CDE:
76 . > */
77 .
78 . ** (1) make an identifier for your data (in stata, "gen id=_n")*/
79 . gen id=_n
80 .
81 . ** (2) make 3 copies of every observation (in stata, use "expand 3"); now you
82 . ** have 2 fake copies of each observation and one real copy.
83 . expand 3
84 . (200,000 observations created)
85 .
86 . ** (3) for the first "fake" copy of each observation, set x to 0 and m to 0
87 . ** and y to . (missing)
88 . sort id
89 .
90 . by id: gen copy=_n
91 .
92 . replace m=0 if copy==2
93 . (100,000 real changes made)
94 .
95 . replace x=0 if copy==2
96 . (49,703 real changes made)
97 .
98 . replace y=. if copy==2
99 . (100,000 real changes made, 100,000 to missing)
100 .
101 . ** (4) for the second "fake" copy of each observation, set x to 1, m to 0 and
102 . ** y to . (missing)
103 . replace m=0 if copy==3
104 . (100,000 real changes made)
105 .
106 . replace x=1 if copy==3
107 . (50,297 real changes made)
108 .
109 . replace y=. if copy==3
110 . (100,000 real changes made, 100,000 to missing)
111 .
112 . ** (5) estimate a regression model predicting the outcome as a function of
113 . ** exposure, mediator, the interaction of the exposure and mediator,
114 . ** and the mediator-outcome confounder (C), using only the real observations.
115 .
116 . gen mx=m*x
117 .
118 . reg y x c m mx if copy==1

```

Source	SS	df	MS	Number of obs	=	100,000
Model	523065.141	4	130766.285	F(4, 99995)	>	99999.00
Residual	99179.098	99,995	.991840572	Prob > F	=	0.0000
				R-squared	=	0.8406
				Adj R-squared	=	0.8406
Total	622244.239	99,999	6.22250461	Root MSE	=	.99591

	y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
	x	1.305609	.0083532	156.30	0.000	1.289236	1.321981
	c	.4976642	.0037928	131.21	0.000	.4902305	.505098
	m	.798887	.0027249	293.18	0.000	.7935462	.8042277
	mx	-.002074	.0034961	-0.59	0.553	-.0089262	.0047783
	_cons	-.0017138	.0044408	-0.39	0.700	-.0104177	.00699

```

104 .
105 . ** (6) for the first fake copy of each observation, use the predict statement
106 . ** to predict the counterfactual value of y, setting x to 0 and m to 0
107 . predict cf_y_x0_m0 if copy==2
    (option xb assumed; fitted values)
    (200,000 missing values generated)

```

```

108 .
109 . ** (7) for the second fake copy of each observation, use the predict statement
110 . ** to predict the counterfactual value of y setting x to 1 and m to 0
111 . predict cf_y_x1_m0 if copy==3
    (option xb assumed; fitted values)
    (200,000 missing values generated)

```

```

112 .
113 . ** (8) estimate the controlled direct effect of x on y, setting m to 0
114 . sum cf_y_x0_m0 if copy==2

```

Variable	Obs	Mean	Std. Dev.	Min	Max
cf_y_x0_m0	100,000	-.0028079	.4964116	-2.101388	2.247978

```

115 . scalar mean_cf_y_x0_m0=r(mean)

```

```

116 . sum cf_y_x1_m0 if copy==3

```

Variable	Obs	Mean	Std. Dev.	Min	Max
cf_y_x1_m0	100,000	1.302801	.4964116	-.7957797	3.553587

```

117 . scalar mean_cf_y_x1_m0=r(mean)

```

```

118 .
119 . dis in red "Estimated controlled direct effect of x, setting m to 0, is: " round(mean_cf_y_x1_m0)
Estimated controlled direct effect of x, setting m to 0, is: 1.306

```

```

120 . ** this is the same as paramed output

```

```

121 .

```

```

122 . /* Bonus hw if you're having fun.

```

```

>

```

```

> Go back to your original data (before you calculated the CDE*/

```

```

123 . clear

```



```
124 . set seed 4321

125 . set obs 100000
    number of observations (_N) was 0, now 100,000

126 . gen x=runiform()<.5

127 . gen c=rnormal()

128 . gen m=2*x+c+rnormal()*1.5

129 . gen y=1.3*x+0.8*m+0.5*c+rnormal()

130 .
131 . **(1) make an identifier for your data (in stata, "gen id=_n")
132 . gen id=_n

133 .
134 . **(2) make 3 copies of every observation (in stata, use "expand 3"); now you
135 . **have 2 fake copies of each observation and one real copy.
136 . expand 3
    (200,000 observations created)

137 .
138 . **(3) for the first "fake" copy of each observation, set x to 0 and m to .
139 . **and y to .
140 . sort id

141 . by id: gen copy=_n

142 . replace m=. if copy==2
    (100,000 real changes made, 100,000 to missing)

143 . replace x=0 if copy==2
    (49,703 real changes made)

144 . replace y=. if copy==2
    (100,000 real changes made, 100,000 to missing)

145 .
146 . **(4) for the second "fake" copy of each observation, set x to 1, m to . and
147 . ** y to .
148 . replace m=. if copy==3
    (100,000 real changes made, 100,000 to missing)

149 . replace x=1 if copy==3
    (50,297 real changes made)

150 . replace y=. if copy==3
    (100,000 real changes made, 100,000 to missing)

151 .
152 . **(5) estimate a regression model predicting the mediator as a function of
```

```

153 . **x and c, using only the real observations
154 . gen mx = m*x
      (200,000 missing values generated)

```

```

155 . reg m x c if copy==1

```

Source	SS	df	MS	Number of obs	=	100,000
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```

156 .
157 . ** (6) predict cf_m_x0 in the first fake copy
158 . *this gives counterfactual m when exposure is set to 0
159 . predict cf_m_x0 if copy==2
      (option xb assumed; fitted values)
      (200,000 missing values generated)

```

```

160 .
161 . ** (7) predict cf_m_x1 in the second fake copy
162 . *this gives counterfactual m when exposure is set to 1
163 . predict cf_m_x1 if copy==3
      (option xb assumed; fitted values)
      (200,000 missing values generated)

```

```

164 .
165 . ** (8) estimate a regression model predicting the outcome as a function of
166 . ** exposure, mediator, the interaction of the exposure and mediator,
167 . ** and the mediator-outcome confounder (C), using only the real observation
168 . reg y x m mx c if copy==1

```

Source	SS	df	MS	Number of obs	=	100,000
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c	.4976642	.0037928	131.21	0.000	.4902305	.505098
_cons	-.0017138	.0044408	-0.39	0.700	-.0104177	.00699

```

169 .
170 . ** (9) in the first fake copy, set m to cf_m_x0 and set x to 1
171 . replace m=cf_m_x0 if copy==2
    (100,000 real changes made)

172 . replace x=1 if copy==2
    (100,000 real changes made)

173 . replace mx=m*x if copy==2
    (100,000 real changes made)

174 .
175 . ** (10) in the second fake copy, set m to cf_m_x1
176 . replace m=cf_m_x1 if copy==3
    (100,000 real changes made)

177 . replace mx=m*x if copy==3
    (100,000 real changes made)

178 .
179 . ** (11) in the first fake copy, predict y based on the regression model
180 . ** in (8), to estimate cf_y_x1_cf_m_x0
181 . predict cf_y_x1_cf_m_x0 if copy==2
    (option xb assumed; fitted values)
    (200,000 missing values generated)

182 .
183 . ** (12) in the second fake copy, predict y based on the regression model in (8),
184 . ** to estimate cf_y_x1_cf_m_x1
185 . predict cf_y_x1_cf_m_x1 if copy==3
    (option xb assumed; fitted values)
    (200,000 missing values generated)

186 .
187 . ** (13) estimate the natural indirect effect of x on y, mediated by m
188 . * Natural indirect effect is when exposure status is not changing
189 . * and mediator is changing. In this case exposure is set at 1 and we are
190 . * comparing outcome under potential mediators at exposed and unexposed.
191 . * Among exposed what would the outcome be if mediator had the potential value
192 . * under exposure and what would the outcome be if mediator had the potential value
193 . * under no exposure. Contract of the potential outcomes.
194 . sum cf_y_x1_cf_m_x0 if copy==2

```

Variable	Obs	Mean	Std. Dev.	Min	Max
cf_y_x1_cf~0	100,000	1.298033	1.291807	-4.163082	7.155231

```

195 . scalar mean_cf_y_x1_cf_m_x0=r(mean)

```

```

196 . sum cf_y_x1_cf_m_x1 if copy==3

```

Variable	Obs	Mean	Std. Dev.	Min	Max
cf_y_x1_cf~1	100,000	2.89784	1.291807	-2.563275	8.755038

```
197 . scalar mean_cf_y_x1_cf_m_x1=r(mean)
198 .
199 . dis in red "Estimated natural indirect effect of x on y, mediated by m is: " round(mean_cf_y_x1
Estimated natural indirect effect of x on y, mediated by m is: 1.6
200 .
201 . ** This is the same as the paramed output
202 . *sort copy
203 . *by copy: sum
204 . log close
      name: <unnamed>
      log: C:\Users\z_iza\Desktop\PhD\Classes\Epi III\Session 7\mediation.smcl
      log type: smcl
      closed on: 21 May 2019, 16:02:17
```
