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### **Supplemental Material**

#### **Bias Amplification in Epidemiologic Analysis of Exposure to Mixtures**

Marc G. Weisskopf, Ryan M. Seals, and Thomas F. Webster

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Results are organized by DAG (refer to figures). DAG-specific assumptions are listed at the beginning of each section. Results are given for expected values of the regression coefficients  $b_i$  (for exposure  $X_i$ ) under the usual assumptions for linear regression. Some results are elementary.

For simplicity, assume variables are standardized (centered and variance=1). For DAG 1, we provide results relaxing this assumption. A similar procedure can be followed to generalize results for other cases.

The results for inequalities can depend on the signs of coefficients as multiplying or dividing by negative numbers reverses the direction of inequalities.

### **DAG in Figure 1**

$$Y = \beta_0 + c_1 X_1 + \varepsilon$$

General case allowing for exposure variables with variance not equal to one (i.e. not standardized)

#### **Single exposure analyses:**

$$b_1 = \frac{\text{cov}[X_1, Y]}{\text{var}[X_1]} = \frac{\text{cov}[X_1, \beta_0 + c_1 X_1 + \varepsilon]}{\text{var}[X_1]} = \frac{c_1 \text{var}[X_1]}{\text{var}[X_1]} = c_1$$

$$b_2 = \frac{\text{cov}[X_2, Y]}{\text{var}[X_2]} = \frac{\text{cov}[X_2, \beta_0 + c_1 X_1 + \varepsilon]}{\text{var}[X_2]} = \frac{c_1 \text{cov}[X_1, X_2]}{\text{var}[X_2]}$$

#### **Mutually adjusted analysis:**

$$b_1 = \frac{\text{var}[X_2] \text{cov}[X_1, Y] - \text{cov}[X_1, X_2] \text{cov}[X_2, Y]}{\text{var}[X_1] \text{var}[X_2] - \text{cov}^2[X_1, X_2]} = \frac{\text{var}[X_2] (c_1 \text{var}[X_1]) - \text{cov}[X_1, X_2] (c_1 \text{cov}[X_1, X_2])}{\text{var}[X_1] \text{var}[X_2] - \text{cov}^2[X_1, X_2]} = c_1$$

$$b_2 = \frac{\text{var}[X_1] \text{cov}[X_2, Y] - \text{cov}[X_1, X_2] \text{cov}[X_1, Y]}{\text{var}[X_1] \text{var}[X_2] - \text{cov}^2[X_1, X_2]} = \frac{\text{var}[X_1] (c_1 \text{cov}[X_1, X_2]) - \text{cov}[X_1, X_2] (c_1 \text{var}[X_1])}{\text{var}[X_1] \text{var}[X_2] - \text{cov}^2[X_1, X_2]} = 0$$

When exposure variances equal one (i.e. standardized), the above equations simplify with  $\text{cov}[X_1, X_2] = r_{12}$

#### **Single exposure analyses:**

$$b_1 = \frac{\text{cov}[X_1, Y]}{\text{var}[X_1]} = \text{cov}[X_1, \beta_0 + c_1 X_1 + \varepsilon] = c_1$$

$$b_2 = \frac{\text{cov}[X_2, Y]}{\text{var}[X_2]} = \text{cov}[X_2, \beta_0 + c_1 X_1 + \varepsilon] = c_1 \text{cov}[X_1, X_2] = c_1 r_{12}$$

Mutually adjusted analysis:

$$b_1 = \frac{\text{var}[X_2]\text{cov}[X_1, Y] - \text{cov}[X_1, X_2]\text{cov}[X_2, Y]}{\text{var}[X_1]\text{var}[X_2] - \text{cov}^2[X_1, X_2]} = \frac{c_1 - r_{12}(c_1 r_{12})}{1 - r_{12}^2} = c_1$$

$$b_2 = \frac{\text{var}[X_1]\text{cov}[X_2, Y] - \text{cov}[X_1, X_2]\text{cov}[X_1, Y]}{\text{var}[X_1]\text{var}[X_2] - \text{cov}^2[X_1, X_2]} = \frac{c_1 r_{12} - r_{12}(c_1)}{1 - r_{12}^2} = 0$$

**DAG in Figure 2a**

$$Y = \beta_0 + c_1 X_1 + c_3 U' + \varepsilon$$

$$\text{cov}[X_1, U'] = c_2, \quad \text{cov}[X_2, U'] = 0 \quad \text{since } X_1 \text{ is a collider on } X_2 \leftarrow U \rightarrow X_1 \leftarrow U'$$

Single exposure analyses:

$$b_1 = \text{cov}[X_1, Y] = \text{cov}[X_1, \beta_0 + c_1 X_1 + c_3 U' + \varepsilon] = c_1 + c_3 \text{cov}[X_1, U'] = c_1 + c_3 c_2$$

$$b_2 = \text{cov}[X_2, Y] = \text{cov}[X_2, \beta_0 + c_1 X_1 + c_3 U' + \varepsilon] = c_1 \text{cov}[X_1, X_2] + c_3 \text{cov}[X_2, U'] = c_1 r_{12}$$

Mutually adjusted analysis:

$$b_1 = \frac{\text{cov}[X_1, Y] - r_{12} \text{cov}[X_2, Y]}{1 - r_{12}^2} = \frac{(c_1 + c_3 c_2) - r_{12}(c_1 r_{12})}{1 - r_{12}^2} = c_1 + \frac{c_3 c_2}{1 - r_{12}^2}$$

$$b_2 = \frac{\text{cov}[X_2, Y] - r_{12} \text{cov}[X_1, Y]}{1 - r_{12}^2} = \frac{(c_1 r_{12}) - r_{12}(c_1 + c_3 c_2)}{1 - r_{12}^2} = -\frac{r_{12} c_3 c_2}{1 - r_{12}^2}$$

The sign of  $b_2$  will flip when adjusting for  $X_1$  if  $c_1$  and  $c_2 c_3$  have the same sign.

The absolute value of the adjusted  $b_2$  exceeds the crude estimate when:

$$\left| -\frac{r_{12} c_2 c_3}{1 - r_{12}^2} \right| = \frac{r_{12} c_2 c_3}{1 - r_{12}^2} > r_{12} c_1 \leftrightarrow \frac{c_2 c_3}{1 - r_{12}^2} > c_1 \quad \text{provided } r_{12} > 0, c_1 > 0, c_2 c_3 > 0$$

Other cases can be derived when  $r_{12}$ ,  $c_1$ , or  $c_2 c_3 < 0$ , recalling that inequalities reverse direction when multiplying or dividing by negative numbers.

**DAG in Figure 2b**

The derivation is identical to 2a with  $Z$  replacing  $X_2$ ,  $c_4$  replacing  $r_{12}$ .

**DAG in Figure 3a**

This is a special case of 2a with  $c_1 = 0$ .

### **DAG in Figure 3b**

$$Y = \beta_0 + c_1X_1 + c_4X_2 + c_3U' + \varepsilon$$
$$\text{cov}[X_1, U'] = c_2, \quad \text{cov}[X_2, U'] = 0$$

### **Single exposure analyses:**

$$b_1 = \text{cov}[X_1, Y] = \text{cov}[X_1, \beta_0 + c_1X_1 + c_4X_2 + c_3U' + \varepsilon] = c_1 + c_4r_{12} + c_3 \text{cov}[X_1, U'] = c_1 + c_4r_{12} + c_3c_2$$
$$b_2 = \text{cov}[X_2, Y] = \text{cov}[X_2, \beta_0 + c_1X_1 + c_4X_2 + c_3U' + \varepsilon] = c_1r_{12} + c_4 + c_3 \text{cov}[X_2, U'] = c_1r_{12} + c_4$$

### **Mutually adjusted analysis:**

$$b_1 = \frac{\text{cov}[X_1, Y] - r_{12} \text{cov}[X_2, Y]}{1 - r_{12}^2} = \frac{(c_1 + c_4r_{12} + c_3c_2) - r_{12}(c_1r_{12} + c_4)}{1 - r_{12}^2} = c_1 + \frac{c_3c_2}{1 - r_{12}^2}$$
$$b_2 = \frac{\text{cov}[X_2, Y] - r_{12} \text{cov}[X_1, Y]}{1 - r_{12}^2} = \frac{(c_1r_{12} + c_4) - r_{12}(c_1 + c_4r_{12} + c_3c_2)}{1 - r_{12}^2} = c_4 - \frac{c_2c_3r_{12}}{1 - r_{12}^2}$$

$b_1$ : the bias of the crude estimate exceeds bias of the adjusted estimate when:

$$r_{12}c_4 + c_2c_3 > \frac{c_2c_3}{1 - r_{12}^2} \leftrightarrow r_{12}c_4 > c_2c_3 \left( \frac{r_{12}^2}{1 - r_{12}^2} \right) \leftrightarrow c_4 > c_2c_3 \left( \frac{r_{12}}{1 - r_{12}^2} \right) \text{ if } r_{12}, c_4, c_2c_3 > 0$$

The same condition implies that the adjusted  $b_2$  will be positive but biased toward zero. Other cases can be derived when  $r_{12} < 0$ ,  $c_4 < 0$  or  $c_2c_3 < 0$ .

### **DAG in Figure 4a**

$$Y = \beta_0 + c_1X_1 + c_3U' + \varepsilon$$
$$\text{cov}[X_1, X_2] = r_{12}, \quad \text{cov}[X_1, X_3] = r_{13}, \quad \text{cov}[X_2, X_3] = r_{23}$$
$$\text{cov}[X_1, U'] = c_2$$
$$\text{cov}[X_2, U'] = \text{cov}[X_3, U'] = 0$$

### **Single exposure analyses:**

$$b_1 = \text{cov}[X_1, Y] = \text{cov}[X_1, \beta_0 + c_1X_1 + c_3U' + \varepsilon] = c_1 + c_3 \text{cov}[X_1, U'] = c_1 + c_3c_2$$
$$b_2 = \text{cov}[X_2, Y] = \text{cov}[X_2, \beta_0 + c_1X_1 + c_3U' + \varepsilon] = c_1r_{12} + c_3 \text{cov}[X_2, U'] = c_1r_{12}$$
$$b_3 = \text{cov}[X_3, Y] = \text{cov}[X_3, \beta_0 + c_1X_1 + c_3U' + \varepsilon] = c_1r_{13} + c_3 \text{cov}[X_3, U'] = c_1r_{13}$$

### **Mutually adjusted for $X_1$ and $X_i$ (either $X_2$ or $X_3$ ):**

$$b_1 = \frac{\text{cov}[X_1, Y] - r_{1i} \text{cov}[X_i, Y]}{1 - r_{1i}^2} = \frac{(c_1 + c_3c_2) - r_{1i}(c_1r_{1i})}{1 - r_{1i}^2} = c_1 + \frac{c_3c_2}{1 - r_{1i}^2}$$
$$b_i = \frac{\text{cov}[X_i, Y] - r_{1i} \text{cov}[X_1, Y]}{1 - r_{1i}^2} = \frac{(c_1r_{1i}) - r_{1i}(c_1 + c_3c_2)}{1 - r_{1i}^2} = -\frac{r_{1i}c_3c_2}{1 - r_{1i}^2}$$

Mutually adjusted for all three exposures (ignoring the constant coefficient  $b_0$ ):

$$b = (X'X)^{-1} X'Y$$

$$A = X'X = \begin{pmatrix} 1 & r_{12} & r_{13} \\ r_{12} & 1 & r_{23} \\ r_{13} & r_{23} & 1 \end{pmatrix}$$

$$X'Y = \begin{pmatrix} \text{cov}[X_1, Y] \\ \text{cov}[X_2, Y] \\ \text{cov}[X_3, Y] \end{pmatrix} = \begin{pmatrix} c_1 + c_3 c_2 \\ c_1 r_{12} \\ c_1 r_{13} \end{pmatrix}$$

$$\det[A] = 1 - r_{12}^2 - r_{13}^2 - r_{23}^2 + 2r_{12}r_{13}r_{23}$$

$$b = \frac{1}{\det[A]} \begin{pmatrix} 1 - r_{23}^2 & r_{13}r_{23} - r_{12} & r_{12}r_{23} - r_{13} \\ r_{13}r_{23} - r_{12} & 1 - r_{13}^2 & r_{12}r_{13} - r_{23} \\ r_{12}r_{23} - r_{13} & r_{12}r_{13} - r_{23} & 1 - r_{12}^2 \end{pmatrix} \begin{pmatrix} c_1 + c_3 c_2 \\ c_1 r_{12} \\ c_1 r_{13} \end{pmatrix}$$

$$b_1 = \frac{(1 - r_{23}^2)(c_1 + c_3 c_2) + (r_{13}r_{23} - r_{12})c_1 r_{12} + (r_{12}r_{23} - r_{13})c_1 r_{13}}{\det[A]} = c_1 + \frac{(1 - r_{23}^2)c_3 c_2}{\det[A]}$$

$$b_2 = \frac{(r_{13}r_{23} - r_{12})(c_1 + c_3 c_2) + (1 - r_{13}^2)c_1 r_{12} + (r_{12}r_{13} - r_{23})c_1 r_{13}}{\det[A]} = \frac{(r_{13}r_{23} - r_{12})c_3 c_2}{\det[A]}$$

$$b_3 = \frac{(r_{12}r_{23} - r_{13})(c_1 + c_3 c_2) + (r_{12}r_{13} - r_{23})c_1 r_{12} + (1 - r_{12}^2)c_1 r_{13}}{\det[A]} = \frac{(r_{12}r_{23} - r_{13})c_3 c_2}{\det[A]}$$

Adjusting for  $X_3$  amplifies the bias for  $b_1$  beyond adjusting for just  $X_2$  when:

$$\frac{(1 - r_{23}^2)c_2 c_3}{1 - r_{12}^2 - r_{13}^2 - r_{23}^2 + 2r_{12}r_{13}r_{23}} > \frac{c_2 c_3}{1 - r_{12}^2} \leftrightarrow (1 - r_{23}^2)(1 - r_{12}^2) > 1 - r_{12}^2 - r_{13}^2 - r_{23}^2 + 2r_{12}r_{13}r_{23},$$

$$\text{if } \det[A] > 0, c_2 c_3 > 0$$

$$\leftrightarrow 1 - r_{12}^2 - r_{23}^2 + r_{12}^2 r_{23}^2 > 1 - r_{12}^2 - r_{13}^2 - r_{23}^2 + 2r_{12}r_{13}r_{23} \leftrightarrow r_{12}^2 r_{23}^2 + r_{13}^2 - 2r_{12}r_{13}r_{23} = (r_{12}r_{23} - r_{13})^2 > 0$$

Note that the determinant of the exposure correlation matrix is the denominator of the amplification factor (as it also is for 2 exposure variables).

$\det[A] > 0$  because exposure variance-covariance matrices are positive semidefinite, positive definite if non-singular (Horn RA and Johnson CR. *Matrix Analysis*. Cambridge University Press 1985; pg 392, 396-399). Therefore, the amplification is always larger for  $b_1$  unless  $r_{12}r_{23} = r_{13}$  (and similarly for adjusting for  $X_2$  beyond adjusting for  $X_3$ ). We hypothesize that this will also be true for higher order systems.

### **Addition to DAG in Figure 4a of an arrow from $X_2$ to $Y$**

We'll analyze the effect on  $b_1$  (analyses for  $b_2$  and  $b_3$  not shown). No new computations are required as the results can be derived from earlier DAGs, i.e., adding  $X_3$  does not change the pathways between  $X_1$  and  $Y$  or  $X_2$  and  $Y$ . The crude estimate of  $b_1$  is equivalent to that in DAG 3b:

$$b_1 = c_1 + r_{12}c_4 + c_2c_3$$

The estimate of  $b_1$  adjusted for  $X_2$  alone is also equivalent to that in DAG 3b:

$$\text{_____ } b_1 = c_1 + \frac{c_2c_3}{1-r_{12}^2}$$

The estimate of  $b_1$  adjusted for  $X_2$  and  $X_3$  is the same as that given above for DAG 4a:

$$\text{_____ } b_1 = c_1 + \frac{(1-r_{23}^2)c_2c_3}{\det[A]}$$

Adding the arrow from  $X_2$  to  $Y$  does not change this computation because the new pathway from  $X_3$  to  $Y$  through  $X_2$  is blocked.

Compared to DAG 3b, the confounding caused by  $U'$  may be further amplified by adding  $X_3$  and certainly would be if  $r_{23}=0$  (as in DAG 4b). Similar to DAG 3b, the choice of whether to adjust the  $X_1$ - $Y$  association for both  $X_2$  and  $X_3$  requires a balancing of confounding through  $X_2$  vs. amplification of confounding through  $U'$ , but the latter may now be even larger. The bias of the crude  $b_1$  is larger than fully adjusted

$$\text{when } r_{12}c_4 + c_2c_3 > \frac{c_2c_3(1-r_{23}^2)}{\det[A]} \leftrightarrow r_{12}c_4 > \frac{c_2c_3(1-r_{23}^2 - \det[A])}{\det[A]} \leftrightarrow c_4 > \frac{c_2c_3(1-r_{23}^2 - \det[A])}{r_{12}\det[A]} \text{ if } r_{12}, c_4, c_2c_3 > 0$$

#### **DAG in Figure 4b:**

This is a special case of the previous derivation with  $r_{23}=0$ . The amplification factor for  $b_1$  then depends solely on  $\det(A)$ .

#### **DAG in Figure 5a**

$$Y = b_0 + c_1X_1 + c_3U' + \varepsilon$$

$$\text{cov}[X_1, U'] = c_2c_4$$

$$\text{cov}[X_2, U'] = c_2c_5$$

$$\text{cov}[X_1, X_2] = c_4c_5 = r_{12} \text{ since variables are standardized}$$

#### **Single exposure analyses:**

$$b_1 = \text{cov}[X_1, Y] = \text{cov}[X_1, b_0 + c_1X_1 + c_3U'] = c_1 + c_3 \text{cov}[X_1, U'] = c_1 + c_3c_2c_4$$

$$b_2 = \text{cov}[X_2, Y] = \text{cov}[X_2, b_0 + c_1X_1 + c_3U'] = c_1r_{12} + c_3 \text{cov}[X_2, U'] = c_1r_{12} + c_3c_2c_5$$

#### **Mutually adjusted analysis:**

$$b_1 = \frac{\text{cov}[X_1, Y] - r_{12} \text{cov}[X_2, Y]}{1 - r_{12}^2} = \frac{(c_1 + c_3c_2c_4) - r_{12}(c_1r_{12} + c_3c_2c_5)}{1 - r_{12}^2}$$

$$= c_1 + c_3c_2 \left( \frac{c_4 - r_{12}c_5}{1 - r_{12}^2} \right) = c_1 + c_3c_2c_4 \left( \frac{1 - c_5^2}{1 - c_4^2c_5^2} \right)$$

$$b_2 = \frac{\text{cov}[X_2, Y] - r_{12} \text{cov}[X_1, Y]}{1 - r_{12}^2} = \frac{(c_1r_{12} + c_3c_2c_5) - r_{12}(c_1 + c_3c_2c_4)}{1 - r_{12}^2}$$

$$= c_3c_2 \left( \frac{c_5 - r_{12}c_4}{1 - r_{12}^2} \right) = c_3c_2c_5 \left( \frac{1 - c_4^2}{1 - c_4^2c_5^2} \right)$$

$b_1$ : adjusted bias < crude bias when:

$$c_2c_3c_4 \left( \frac{1-c_5^2}{1-c_4^2c_5^2} \right) < c_2c_3c_4 \leftrightarrow 1-c_5^2 < 1-c_4^2c_5^2 \leftrightarrow c_4^2c_5^2 < c_5^2 \leftrightarrow c_4^2 < 1 \quad \text{if } c_2c_3c_4 > 0$$

b<sub>2</sub>: adjusted bias < crude bias when:

$$c_2c_3c_5 \left( \frac{1-c_4^2}{1-c_4^2c_5^2} \right) < c_1c_4c_5 + c_2c_3c_5 \leftrightarrow c_2c_3 \left( \frac{1-c_4^2}{1-c_4^2c_5^2} - 1 \right) < c_1c_4 \leftrightarrow c_2c_3 \left( \frac{-c_4^2 + c_4^2c_5^2}{1-c_4^2c_5^2} \right) < c_1c_4$$

$$\leftrightarrow c_2c_3c_4^2 \left( \frac{c_5^2-1}{1-c_4^2c_5^2} \right) < 0 < c_1c_4 \quad \text{since } c_5^2-1 < 0 \text{ and } 1-c_4^2c_5^2 > 0, \quad \text{if } c_5, c_2c_3, c_1c_4 > 0$$

Other cases can be derived when  $c_5$ ,  $c_2c_3$ , or  $c_1c_4 < 0$ .

### DAG in Figure 5b

$$Y = b_0 + c_1X_1 + c_3U' + \varepsilon$$

$$\text{cov}[X_1, U'] = c_2$$

$$\text{cov}[X_2, U'] = c_4$$

$$\text{cov}[X_1, X_2] = c_2c_4 = r_{12} \quad \text{since variables are standardized}$$

### Single exposure analyses:

$$b_1 = \text{cov}[X_1, Y] = \text{cov}[X_1, b_0 + c_1X_1 + c_3U'] = c_1 + c_3 \text{cov}[X_1, U'] = c_1 + c_3c_2$$

$$b_2 = \text{cov}[X_2, Y] = \text{cov}[X_2, b_0 + c_1X_1 + c_3U'] = c_1r_{12} + c_3 \text{cov}[X_2, U'] = c_1r_{12} + c_3c_4 = c_1c_2c_4 + c_3c_4$$

### Mutually adjusted analysis:

$$b_1 = \frac{\text{cov}[X_1, Y] - r_{12} \text{cov}[X_2, Y]}{1 - r_{12}^2} = \frac{(c_1 + c_3c_2) - r_{12}(c_1r_{12} + c_3c_4)}{1 - r_{12}^2}$$

$$= c_1 + \frac{c_3(c_2 - r_{12}c_4)}{1 - r_{12}^2} = c_1 + c_3c_2 \left( \frac{1 - c_4^2}{1 - c_2^2c_4^2} \right)$$

$$b_2 = \frac{\text{cov}[X_2, Y] - r_{12} \text{cov}[X_1, Y]}{1 - r_{12}^2} = \frac{(c_1r_{12} + c_3c_4) - r_{12}(c_1 + c_3c_2)}{1 - r_{12}^2}$$

$$= \frac{c_3(c_4 - r_{12}c_2)}{1 - r_{12}^2} = c_3c_4 \left( \frac{1 - c_2^2}{1 - c_2^2c_4^2} \right)$$

### DAG in Figure 5c

$$Y = b_0 + c_1X_1 + c_3U' + \varepsilon$$

$$\text{cov}[X_1, U'] = c_2 \quad \text{because } X_2 \text{ is a collider on } X_1 \leftarrow U \rightarrow X_2 \leftarrow U'$$

$$\text{cov}[X_2, U'] = c_4 \quad \text{because } X_1 \text{ is a collider on } X_2 \leftarrow U \rightarrow X_1 \leftarrow U'$$

$$\text{cov}[X_1, X_2] = r_{12} \quad \text{includes components on both } X_1 \leftarrow U \rightarrow X_2 \text{ and } X_1 \leftarrow U' \rightarrow X_2$$

### Single exposure analyses:

$$b_1 = \text{cov}[X_1, Y] = \text{cov}[X_1, b_0 + c_1 X_1 + c_3 U' + \varepsilon] = c_1 + c_3 \text{cov}[X_1, U'] = c_1 + c_3 c_2$$

$$b_2 = \text{cov}[X_2, Y] = \text{cov}[X_2, b_0 + c_1 X_1 + c_3 U' + \varepsilon] = c_1 r_{12} + c_3 \text{cov}[X_2, U'] = r_{12} c_1 + c_3 c_4$$

### Mutually adjusted analysis:

$$\begin{aligned} b_1 &= \frac{\text{cov}[X_1, Y] - r_{12} \text{cov}[X_2, Y]}{1 - r_{12}^2} = \frac{(c_1 + c_3 c_2) - r_{12} (c_1 r_{12} + c_3 c_4)}{1 - r_{12}^2} \\ &= c_1 + \frac{c_3 (c_2 - r_{12} c_4)}{1 - r_{12}^2} = c_1 + \frac{c_2 c_3}{1 - r_{12}^2} \left( 1 - r_{12} \frac{c_4}{c_2} \right) \\ b_2 &= \frac{\text{cov}[X_2, Y] - r_{12} \text{cov}[X_1, Y]}{1 - r_{12}^2} = \frac{(c_1 r_{12} + c_3 c_4) - r_{12} (c_1 + c_3 c_2)}{1 - r_{12}^2} \\ &= \frac{c_3 (c_4 - r_{12} c_2)}{1 - r_{12}^2} = \frac{c_3 c_4}{1 - r_{12}^2} \left( 1 - r_{12} \frac{c_2}{c_4} \right) = -\frac{c_2 c_3}{1 - r_{12}^2} \left( r_{12} - \frac{c_4}{c_2} \right) = -\frac{r_{12} c_2 c_3}{1 - r_{12}^2} \left( 1 - \frac{c_4}{r_{12} c_2} \right) \end{aligned}$$

### DAG in Figure 5d

$$Y = b_0 + c_1 X_1 + c_5 X_2 + c_3 U' + \varepsilon$$

$$\text{cov}[X_1, U'] = c_2 \quad \text{because } X_2 \text{ is a collider on } X_1 \leftarrow U \rightarrow X_2 \leftarrow U'$$

$$\text{cov}[X_2, U'] = c_4 \quad \text{because } X_1 \text{ is a collider on } X_2 \leftarrow U \rightarrow X_1 \leftarrow U'$$

$$\text{cov}[X_1, X_2] = r_{12} \quad \text{includes components on both } X_1 \leftarrow U \rightarrow X_2 \text{ and } X_1 \leftarrow U' \rightarrow X_2$$

### Single exposure analysis:

$$b_1 = \text{cov}[X_1, Y] = \text{cov}[X_1, b_0 + c_1 X_1 + c_5 X_2 + c_3 U' + \varepsilon] = c_1 + c_5 r_{12} + c_3 \text{cov}[X_1, U'] = c_1 + c_5 r_{12} + c_3 c_2$$

$$b_2 = \text{cov}[X_2, Y] = \text{cov}[X_2, b_0 + c_1 X_1 + c_5 X_2 + c_3 U' + \varepsilon] = c_1 r_{12} + c_5 + c_3 \text{cov}[X_2, U'] = r_{12} c_1 + c_5 + c_3 c_4$$

### Mutually adjusted analysis:

$$\begin{aligned} b_1 &= \frac{\text{cov}[X_1, Y] - r_{12} \text{cov}[X_2, Y]}{1 - r_{12}^2} = \frac{(c_1 + r_{12} c_5 + c_3 c_2) - r_{12} (c_1 r_{12} + c_5 + c_3 c_4)}{1 - r_{12}^2} \\ &= c_1 + \frac{c_3 (c_2 - r_{12} c_4)}{1 - r_{12}^2} = c_1 + \frac{c_2 c_3}{1 - r_{12}^2} \left( 1 - r_{12} \frac{c_4}{c_2} \right) \\ b_2 &= \frac{\text{cov}[X_2, Y] - r_{12} \text{cov}[X_1, Y]}{1 - r_{12}^2} = \frac{(c_1 r_{12} + c_5 + c_3 c_4) - r_{12} (c_1 + r_{12} c_5 + c_3 c_2)}{1 - r_{12}^2} \\ &= c_5 + \frac{c_3 (c_4 - r_{12} c_2)}{1 - r_{12}^2} = c_5 + \frac{c_3 c_4}{1 - r_{12}^2} \left( 1 - r_{12} \frac{c_2}{c_4} \right) = c_5 - \frac{c_2 c_3}{1 - r_{12}^2} \left( r_{12} - \frac{c_4}{c_2} \right) = c_5 - \frac{r_{12} c_2 c_3}{1 - r_{12}^2} \left( 1 - \frac{c_4}{r_{12} c_2} \right) \end{aligned}$$



Suppose the crude and adjusted  $b_1$  and  $b_2$  are greater than zero.

**b<sub>1</sub>:** The bias of the crude estimate exceeds bias of the mutually adjusted estimate when

$$\begin{aligned}
 r_{12}c_5 + c_2c_3 &> \frac{c_3(c_2 - r_{12}c_4)}{1 - r_{12}^2} \leftrightarrow r_{12}c_5 > \frac{(c_2c_3 - r_{12}c_3c_4 - (1 - r_{12}^2)c_2c_3)}{1 - r_{12}^2} \leftrightarrow r_{12}c_5 > \frac{(-r_{12}c_3c_4 + r_{12}^2c_2c_3)}{1 - r_{12}^2} \\
 &\leftrightarrow c_5 > \frac{c_3(-c_4 + r_{12}c_2)}{1 - r_{12}^2} \quad \text{if } r_{12} > 0 \\
 &\leftrightarrow c_5 + \frac{c_3(c_4 - r_{12}c_2)}{1 - r_{12}^2} > 0 \\
 &\leftrightarrow \text{adjusted } b_2 > 0
 \end{aligned}$$

**b<sub>2</sub>:** The bias of the crude estimate exceeds bias of the mutually adjusted estimate when

$$\begin{aligned}
 r_{12}c_1 + c_3c_4 &> \frac{c_3(c_4 - r_{12}c_2)}{1 - r_{12}^2} \leftrightarrow r_{12}c_1 > \frac{(c_3c_4 - r_{12}c_2c_3 - (1 - r_{12}^2)c_3c_4)}{1 - r_{12}^2} \leftrightarrow r_{12}c_1 > \frac{(-r_{12}c_2c_3 + r_{12}^2c_3c_4)}{1 - r_{12}^2} \\
 &\leftrightarrow c_1 > \frac{c_3(-c_2 + r_{12}c_4)}{1 - r_{12}^2} \quad \text{if } r_{12} > 0 \\
 &\leftrightarrow c_1 + \frac{c_3(c_2 - r_{12}c_4)}{1 - r_{12}^2} > 0 \\
 &\leftrightarrow \text{adjusted } b_1 > 0
 \end{aligned}$$