

1.

(a)

- Since $E(\bar{u}_i | \bar{x}_i) = E\left[E(\bar{u}_i | x_{i1}, \dots, x_{in}) \mid \bar{x}_i\right]$

$$= E\left[\frac{1}{n_i} \sum_{e=1}^{n_i} E(u_{ie} | x_{i1}, \dots, x_{in}) \mid \bar{x}_i\right]$$

$$= E\left[\frac{1}{n_i} \cdot 0 \mid \bar{x}_i\right]$$

$$= 0,$$

$\hat{\beta}_1$ is unbiased.

For consistency,

$$\text{plim}(\hat{\beta}_1) = \beta_1 + \frac{\text{Cov}(\bar{x}_i, \bar{u}_i)}{\text{Var}(\bar{x}_i)}$$

$$\text{Cov}(\bar{u}_i, \bar{x}_i) = \frac{1}{n_i^2} \sum_{e=1}^{n_i} \sum_{f=1}^{n_i} \text{Cov}(u_{ie}, x_{if})$$

$$= \frac{1}{n_i^2} \sum_{e=1}^{n_i} \sum_{f=1}^{n_i} \text{Cov}(v_{ie}, x_{if}) = 0$$

$\Rightarrow \hat{\beta}_1$ is consistent.

- $\text{Var}(\bar{u}_i) = \sigma_f^2 + \frac{1}{n_i^2} \sum_{e=1}^{n_i} \text{Var}(u_{ie})$ (since are i.i.d.)

$$= \sigma_f^2 + \frac{1}{n_i^2} \cdot \sigma_v^2 \cdot n_i$$

$$= \sigma_f^2 + \frac{\sigma_v^2}{n_i}$$

- $h_i = \sigma_f^2 + \frac{\sigma_v^2}{n_i} \Rightarrow \frac{\bar{x}_i}{\sqrt{n_i}} = \beta_0 \frac{1}{\sqrt{n_i}} + \beta_1 \frac{\bar{x}_i}{\sqrt{n_i}} + \frac{\bar{u}_i}{\sqrt{n_i}}$

$\hat{\beta}_1$ is more efficient.

(b)

- Still unbiased and consistent, because $(v_{i,e}, x_{i,e})$ still i.i.d. and f_i are still i.i.d.

- $\text{Var}(u_{i,e}) = \text{Var}(f_i + v_{i,e}) = \text{Var}(f_i) + \text{Var}(v_{i,e})$

$$= \sigma_f^2 + \sigma_v^2$$

$$\begin{aligned} \text{Cov}(u_{i,e}, u_{j,g}) &= \text{Cov}(f_i, f_j) + \text{Cov}(f_i, v_{j,g}) + \text{Cov}(v_{i,e}, f_j) + \text{Cov}(v_{i,e}, v_{j,g}) \\ &\stackrel{i \neq j}{=} 0 + 0 + 0 + 0 \\ &= 0 \end{aligned}$$

$$\begin{aligned} \text{Cov}(u_{i,e}, u_{i,g}) &= \text{Var}(f_i) + \text{Cov}(f_i, v_{i,g}) + \text{Cov}(v_{i,e}, f_i) + \text{Cov}(v_{i,e}, v_{i,g}) \\ &= \sigma_f^2 + 0 + 0 + 0 \\ &= \sigma_f^2 \end{aligned}$$

- Heteroskedasticity-robust standard errors.

- $\text{Var}(\hat{u}_{i,e}) = \text{Var}(u_{i,e} - \bar{u}_i)$

$$\begin{aligned} &= \text{Var}\left(\frac{n_i-1}{n_i} u_{i,e} - \frac{1}{n_i} \sum_{g=1}^{n_i} u_{i,g}\right) \\ &= \left(1 - \frac{1}{n_i}\right)^2 (\sigma_f^2 + \sigma_v^2) + \frac{1}{n_i^2} \cdot (\sigma_f^2 + \sigma_v^2) (n_i - 1) - 2 \frac{n_i-1}{n_i} \sigma_f^2 \cdot \\ &\quad - 2 \frac{1}{n_i^2} \sigma_f^2 \cdot \frac{(n_i-1)(n_i-2)}{2} \end{aligned}$$

$$= \left(1 - \frac{1}{n_i}\right) \sigma_f^2$$

$$\begin{aligned} \text{Cov}(\hat{u}_{i,e}, \hat{u}_{j,g}) &= \text{Cov}(u_{i,e} - \bar{u}_i, u_{j,g} - \bar{u}_j) = \text{Cov}(u_{i,e}, u_{j,g}) - 2\text{Cov}(u_{i,e}, \bar{u}_j) + \text{Var}(\bar{u}_j) \\ &= \sigma_f^2 - 2 \left(\frac{1}{n_i} (\sigma_f^2 + \sigma_v^2) + \frac{n_i-1}{n_i} \sigma_f^2 \right) + \frac{1}{n_i^2} \cdot (\sigma_f^2 + \sigma_v^2) \cdot n_i + \frac{1}{n_i^2} \sigma_f^2 \cdot n_i(n_i-1) \\ &= 0 \cdot \sigma_f^2 - \frac{1}{n_i} \sigma_v^2 \\ &= -\frac{1}{n_i} \sigma_v^2 \end{aligned}$$

2.

$$\begin{aligned}
 (a) E(y|x=1) &= E(y|x=1, x^*=1) \times P(x^*=1|x=1) + E(y|x=1, x^*=0) \times P(x^*=0|x=1) \\
 &= [\beta_0 + \beta_1 \times 1 + E(u|x=1, x^*=1)] \times P(x^*=1|x=1) + \\
 &\quad [\beta_0 + \beta_1 \times 0 + E(u|x=1, x^*=0)] \times P(x^*=0|x=1) \\
 &= (\beta_0 + \beta_1) P(x^*=1|x=1) + \beta_0 P(x^*=0|x=1)
 \end{aligned}$$

$$\begin{aligned}
 E(y|x=0) &= E(y|x=0, x^*=1) \times P(x^*=1|x=0) + E(y|x=0, x^*=0) \times P(x^*=0|x=0) \\
 &= (\beta_0 + \beta_1) P(x^*=1|x=0) + \beta_0 P(x^*=0|x=0)
 \end{aligned}$$

$$\begin{aligned}
 (b) \hat{\beta}_1 &= \bar{y}_1 - \bar{y}_0 \rightarrow E(y|x=1) - E(y|x=0) \\
 &= \beta_1 \times P(x^*=1|x=1) - \beta_1 \times P(x^*=1|x=0) \\
 &= \beta_1 \times [1 - P(x^*=0|x=1)] - \beta_1 \times [1 - P(x^*=0|x=0)] \\
 &= \beta_1 \times [P(x^*=0|x=0) - P(x^*=0|x=1)]
 \end{aligned}$$

(c) $\hat{\beta}_1 \xrightarrow{p} \beta_1$. Intuition: no misclassification, $\hat{\beta}_1$ estimator is unbiased.

(d) $\hat{\beta}_1 \xrightarrow{p} -\beta_1$. Intuition: If the measurement is totally wrong, then it's actually "right", but reversed.

(e) $\hat{\beta}_1 \xrightarrow{p} 0$. Intuition: The measurement has the same probability of 0 and 1, which is useless for OLS.

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- (a) $y_i(1)$ is the outcome we would observe if i is trained

$y_1(s)$ can be divided into 2 parts, $y_1(0)$ and $y_1(1)$

- (b) Not statistically significant.

No.

- (c) From the regression result, we know d is significantly related to earn96, edule, age and married.

So d is not direct or only variable affecting y.

- (d) $\hat{T}_{ATE} = 3,106,202$, coefficient on d is 2.410547

4.

- (c) Not much.

(d)

- 1) Yes.
 - 2) Yes
 - 3) No.

5.

- (c) se is halved.

(d) se returns to the same level in (b).

$$b. \hat{\beta}_{IV} = \frac{\text{Cov}(z, y)}{\text{Cov}(z, x)} = \frac{\frac{1}{n} \sum_{i=1}^n (z_i - \bar{z})(y_i - \bar{y})}{\frac{1}{n} \sum_{i=1}^n (z_i - \bar{z})(x_i - \bar{x})}$$

$$= \frac{\sum z_i(y_i - \bar{y})}{\sum z_i(x_i - \bar{x})} = \frac{\sum z_i y_i - \bar{y} \sum z_i}{\sum z_i x_i - \bar{x} \sum z_i}$$

$$= \frac{n_1 \bar{y}_1 - \frac{n_0 \bar{y}_0 + n_1 \bar{y}_1}{n_0 + n_1} n_1}{n_1 \bar{x}_1 - \frac{n_0 \bar{x}_0 + n_1 \bar{x}_1}{n_0 + n_1} n_1} = \frac{(n_1^2 + n_0 n_1) \bar{y}_1 - n_0 n_1 \bar{y}_0 - n_1^2 \bar{y}_1}{(n_1^2 + n_0 n_1) \bar{x}_1 - n_0 n_1 \bar{x}_0 - n_1^2 \bar{x}_1}$$

$$= \frac{n_0 n_1}{n_0 + n_1} \cdot \frac{\bar{y}_1 - \bar{y}_0}{\bar{x}_1 - \bar{x}_0}$$

$$= \frac{\bar{y}_1 - \bar{y}_0}{\bar{x}_1 - \bar{x}_0}$$

7.

(a) 0.0813949
(0.004776)

(c) Yes. Since near 4 is relevant for educ.

(d) 0.1703064
(0.0511423)

(e) IV is larger, with also larger se.