

1. Go over my slides on causal inference and determining gains to migration.
2. State and discuss simple linear regression assumptions (SLR1-SLR5).

<b>SLR1 (linearity)</b>	$Y = \beta_0 + \beta_1 X + U$
<b>SLR2 (random sampling)</b>	$\{(X_1, Y_1), \dots, (X_N, Y_N)\}$ is a random sample
<b>SLR3 (variation in treatment)</b>	$\widehat{\text{Var}}(X_i) := \sum_{i=1}^N (X_i - \bar{X})^2 > 0$
<b>SLR4 (mean independence)</b>	$E[U X] = 0$
<b>SLR5 (homoskedasticity)</b>	$\text{Var}(U X) = \sigma^2$

3. If  $\log Y$  denotes log earnings,  $S$  is years of schooling and  $U$  is the error term in the linear population regression function (PRF)  $\log Y = \alpha + \beta \cdot S + U$ , then  $\beta$  is the Mincer (1972) returns to an additional year of education. Answer the following questions.
  - a) What is the least squares estimator  $\hat{\beta}^{OLS}$  of the returns parameter  $\beta$ ?

$$\hat{\beta}^{OLS} = \frac{\widehat{\text{Cov}}(S_i, \log Y_i)}{\widehat{\text{Var}}(S_i)} = \frac{\sum (S_i - \bar{S})(\log Y_i - \overline{\log Y})}{\sum (S_i - \bar{S})^2}$$

- b) Under what assumptions is  $\hat{\beta}^{OLS}$  unbiased for  $\beta$ ? **SLR1 + 2 + 3 + 4**
- c) Under what assumptions is  $\hat{\beta}^{OLS}$  consistent for  $\beta$ ? **SLR1 + 2 + 3 +  $\text{Cov}(S, U) = 0$**

- d) Variation in  $S$  is endogenous whenever it is related to  $U$ . Differentiate log earnings with respect to schooling and show that it does not equal to  $\beta$  if  $S$  is endogenous.

**We write  $\log Y = \alpha + \beta S + U(S)$  to indicate that schooling is endogenous, then**

$$\frac{\partial}{\partial S} \log Y = \beta + \frac{\partial}{\partial S} U(S)$$

**where  $\frac{\partial}{\partial S} U(S)$  is the part of the relationship reflecting selection bias (or why not all the observed correlation we try to estimate is causal).**

4. Prove that conditional independence  $E(U|X) = 0$  implies exogeneity  $\text{Cov}(U, X) = 0$  using the law of iterated expectations  $E[Z] = E_A[E[Z|A]]$ .

$$\begin{aligned} \text{Cov}(U, X) &= E[UX] - E[U]E[X] \\ &= E[UX] - 0 \cdot E[X] \\ &= E_X[E[UX|X]] \\ &= E_X[X \cdot E[U|X]] \\ &= E_X[X \cdot 0] \\ &= 0 \end{aligned}$$