

# Measurement error

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## Measurement error in cross-section OLS

- ▶ Simplest case: one variable cross-section regression

$$y_i = \alpha + \beta x_i^* + \varepsilon_i$$

- ▶ where we observe  $x_i^*$  with measurement error

$$x_i = x_i^* + r_i$$

- ▶ such that  $\text{Cov}(x_i^*, r_i) = 0$  and  $\text{Var}(r) = \sigma_r^2$  (classical errors-in-variables, CEV).
- ▶ The estimated model becomes

$$\begin{aligned}y_i &= \alpha + \beta x_i + \eta_i \\ \eta_i &= -\beta r_i + \varepsilon_i\end{aligned}$$

## Measurement error in cross-section OLS

- ▶ The estimated  $\hat{\beta}_{OLS}$  becomes:

$$p \lim_{N \rightarrow \infty} \hat{\beta}_{OLS} = \frac{\text{Cov}(y_i, x_i)}{\text{Var}(x_i)} = \frac{\text{Cov}(\alpha + \beta x_i - \beta r_i + \varepsilon_i, x_i)}{\text{Var}(x_i)}$$

- ▶ Notice that the first part in the covariance has four items:  $\alpha$ ,  $\beta x_i$ ,  $-\beta r_i$ , and  $\varepsilon$ .

## Measurement error in cross-section OLS

- ▶ Let's go through the relation between each of these 4 parts and the second part in the covariance,  $x_i$ :
  1.  $\alpha$ : this is a constant, so its covariance with anything is zero.
  2.  $\beta x_i$ : This consists of a constant  $\beta$  times the same variable with which we measure the covariance. Thus
$$\text{Cov}(\beta x_i, x_i) = \beta \text{Cov}(x_i, x_i) = \beta \text{Var}(x_i).$$
  3.  $-\beta r_i$ : Again there is a constant,  $-\beta$ . To understand the covariance between  $r_i$  and  $x_i$ , recall that  $x_i = x_i^* + r_i$  and that  $x_i^*$  is uncorrelated with  $r_i$ . Thus we get  $\text{Cov}(-\beta r_i, x_i) = \text{Cov}(-\beta r_i, x_i^* + r_i) = \text{Cov}(-\beta r_i, r_i) = -\beta \text{Var}(r_i) = -\beta \sigma_r^2$ .
  4.  $\varepsilon_i$ : This is uncorrelated with  $x_i^*$  and  $r_i$  and therefore also with  $x_i$ . Thus the covariance between  $\varepsilon_i$  and  $x_i$  is zero.

## Measurement error in cross-section OLS

- ▶ The estimated  $\hat{\beta}_{OLS}$  becomes:

$$\begin{aligned} p \lim_{N \rightarrow \infty} \hat{\beta}_{OLS} &= \frac{\text{Cov}(\alpha + \beta x_i - \beta r_i + \varepsilon_i, x_i)}{\text{Var}(x_i)} \\ &= \frac{0 + \beta \text{Var}(x_i) - \beta \text{Var}(r_i) + 0}{\text{Var}(x_i)} = \beta - \beta \frac{\text{Var}(r_i)}{\text{Var}(x_i)} \end{aligned}$$

- ▶ This can be rewritten to yield

$$= \beta - \beta \frac{\sigma_r^2}{\sigma_x^2} = \beta - \beta \frac{\sigma_r^2}{\sigma_{x^*}^2 + \sigma_r^2} = \beta \frac{\sigma_{x^*}^2}{\sigma_{x^*}^2 + \sigma_r^2}$$

- ▶ where  $\sigma_x^2 = \sigma_{x^*}^2 + \sigma_r^2$  and
- ▶  $\sigma_r^2 / \sigma_x^2 =$  noise-to-signal ratio.
- ▶  $\sigma_{x^*}^2 / (\sigma_{x^*}^2 + \sigma_r^2) =$  reliability ratio.
- ▶  $-\beta \sigma_r^2 / (\sigma_{x^*}^2 + \sigma_r^2) =$  attenuation bias.