

## Large-Sample Properties

- Let's take a few minutes to focus on the asymptotic properties of OLS.
  - These are often called large-sample properties.
  - Many of you will be working with huge datasets, and it's good to summarize how these work.
- We've listed a lot of assumptions that look daunting.
  - If we have a large sample size, we don't need many of the stronger assumptions in the classical model.
  - As long as we have a large sample and use heteroskedasticity-robust standard errors, we generally focus on MLR.1–3 and MLR.4'.

## Crucial Assumptions for Large Samples

### 1. Assumption MLR.1 (linear in parameters)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + u$$

### 2. Assumption MLR.2 (random sampling)

$$\{(x_{i1}, x_{i2}, \dots, x_{ik}, y_i) : i = 1, \dots, n\}$$

Data points are independent draws from population

### 3. Assumption MLR.3 (no perfect collinearity)

### 4. Assumption MLR.4' (exogeneity)

$$\text{Cov}(x_j, u) = 0 \text{ for all } j.$$

## OLS Consistency

- We already know that under MLR.1–3 and MLR.4', OLS estimators are consistent.
  - $\text{plim}_{n \rightarrow \infty} (\hat{\beta}_j) = \beta_j$
- This means that we can always get the right answer if we collect an infinite number of data points.

## Asymptotic Normality

- What about the shape of the distribution?
  - The central limit theorem tells us that our coefficients have an asymptotically normal sampling distribution.
  - The proof is tough, so we'll skip it here, but there's a sketch in an appendix of Wooldridge. (The theorem is stated under MLR.1–MLR.5.)
- **Theorem 5.2 (Asymptotic normality of OLS):**

$$\frac{\hat{\beta}_j - \beta_j}{\text{se}(\hat{\beta}_j)} \overset{a}{\sim} N(0, 1) \text{ also } \text{plim} \hat{\sigma}^2 = \sigma^2$$
- Note that if you use heteroskedasticity-robust standard errors, you can drop MLR.5.

## Asymptotic Normality (cont.)

What does this mean from a practical standpoint?

- As  $n$  increases, sampling distributions become normal.
  - We can't see this because we only get one sample, but the math tells us it's happening.
- Since the  $t$ -distribution is asymptotically normal, it doesn't matter if we use a normal or  $t$ -distribution in stating our theorem.
  - This means that  $t$ -tests are valid for large samples; the same is true for confidence intervals and  $F$ -tests.
- For large samples, there are two key assumptions to focus on.
  - Random sampling: Are the observations correlated in some way, and is there clustering or a time dimension?
  - Exogeneity: Is any  $x$  correlated with the error, and is there some unmeasured factor that ends up in the error that's related to an  $x$ ?

**Most of the rest of this course is about what to do when we can't meet the key assumptions we just discussed.**