Section 3. Simple Regression – Confidence Intervals

- 1. Review: Least Squares Estimators
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1. Review: OLS estimators

The OLS Estimator, Predicted Values, and Residuals

The OLS estimators of the slope β_1 and the intercept β_0 are:

$$\hat{\beta}_{1} = \frac{\sum_{i=1}^{n} (X_{i} - \overline{X})(Y_{i} - \overline{Y})}{\sum_{i=1}^{n} (X_{i} - \overline{X})^{2}} = \frac{s_{XY}}{s_{X}^{2}}$$

$$\hat{\beta}_{0} = \overline{Y} - \hat{\beta}_{1}\overline{X}.$$
(4.8)
(4.9)

The OLS predicted values \hat{Y}_i and residuals \hat{u}_i are:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i, \ i = 1, \dots, n$$
 (4.10)

$$\hat{u}_i = Y_i - \hat{Y}_i, \ i = 1, \dots, n.$$
 (4.11)

The estimated intercept $(\hat{\beta}_0)$, slope $(\hat{\beta}_1)$, and residual (\hat{u}_i) are computed from a sample of *n* observations of X_i and Y_i , i = 1, ..., n. These are estimates of the unknown true population intercept (β_0) , slope (β_1) , and error term (u_i) .

2. OLS Assumptions

The Least Squares Assumptions

$$Y_i = \beta_0 + \beta_1 X_i + u_i, i = 1, ..., n$$
, where:

- 1. The error term u_i has conditional mean zero given X_i , that is, $E(u_i | X_i) = 0$;
- 2. (X_i, Y_i) , i = 1, ..., n are independent and identically distributed (i.i.d.) draws from their joint distribution; and
- 3. (X_i, u_i) have nonzero finite fourth moments.

3. Sampling Properties of OLS estimators

- Unbiased: $E(b_0) = \beta_0$, $E(b_1) = \beta_1$
- Consistent: $plim(b_0) = \beta_0$, $plim(b_1) = \beta_1$
- Asymptotically Normal by the CLT

Derivation

Derivation

Sampling Properties of OLS estimators (cont.)

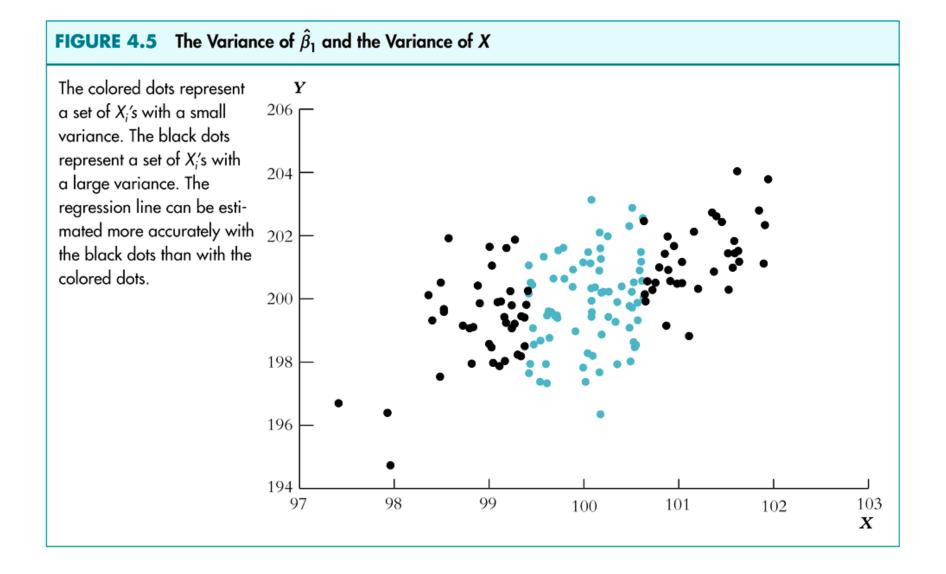
Large-Sample Distributions of $\hat{\beta}_0$ and $\hat{\beta}_1$

If the least squares assumptions in Key Concept 4.3 hold, then in large samples $\hat{\beta}_0$ and $\hat{\beta}_1$ have a jointly normal sampling distribution. The large-sample normal distribution of $\hat{\beta}_1$ is $N(\beta_1, \sigma_{\hat{\beta}_1}^2)$, where the variance of this distribution, $\sigma_{\hat{\beta}_1}^2$, is

$$\sigma_{\hat{\beta}_1}^2 = \frac{1}{n} \frac{\operatorname{var}[(X_i - \mu_X)u_i]}{[\operatorname{var}(X_i)]^2}.$$
(4.14)

The large-sample normal distribution of $\hat{\beta}_0$ is $N(\beta_0, \sigma_{\hat{\beta}_0}^2)$, where

$$\sigma_{\hat{\beta}_0}^2 = \frac{1}{n} \frac{\operatorname{var}(H_i u_i)}{[E(H_i^2)]^2}, \quad \text{where } H_i = 1 - \left(\frac{\mu_X}{E(X_i^2)}\right) X_i.$$
(4.15)



4. Standard Errors

- CLT: $b_1 \operatorname{approx} \sim N(\beta_1, V(b_1))$ $b_0 \operatorname{approx} \sim N(\beta_0, V(b_0))$
- "Standard Errors" are consistent estimators of standard deviations of b_o and b₁. (S&W p. 133, 151,180).
- So "t-statistics" have a standard normal distribution.

5. Confidence Intervals

Confidence Intervals for β_1

A 95% two-sided confidence interval for β_1 is an interval that contains the true value of β_1 with a 95% probability, that is, it contains the true value of β_1 in 95% of all possible randomly drawn samples. Equivalently, it is also the set of values of β_1 that cannot be rejected by a 5% two-sided hypothesis test. When the sample size is large, it is constructed as

95% confidence interval for $\beta_1 = (\hat{\beta}_1 - 1.96SE(\hat{\beta}_1), \hat{\beta}_1 + 1.96SE(\hat{\beta}_1)).$ (4.27)

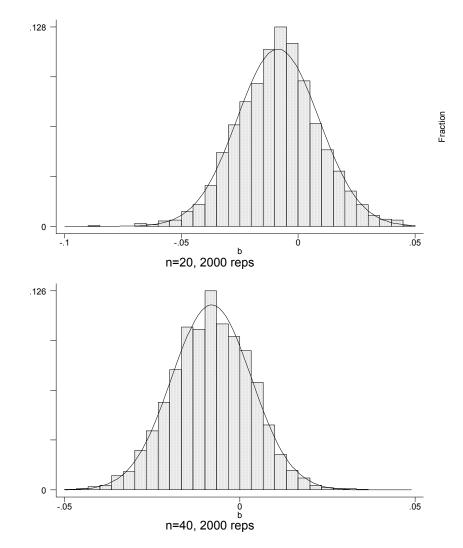
...and the same for β_0

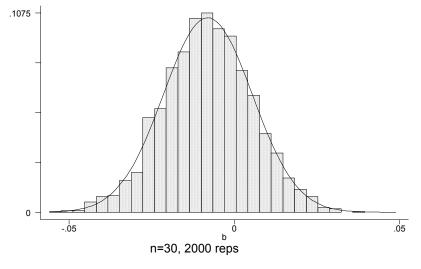
6. CLT demonstrations using Stata

Stata doesn't mind running a regression a few thousand times,
which allows us to observe a sampling distribution for b₁
e.g., bootregh00.do

..and the same for $\mathbf{b_0}$

CLT in action: sampling distributions for b₁





Note: In developing countries this slope is about -0.2 children per year of education. Vg

Fraction

Next time..

• Omitted variable bias