Previously on Quantitative Methods...

Linear regression model in the population:

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

OLS estimators of

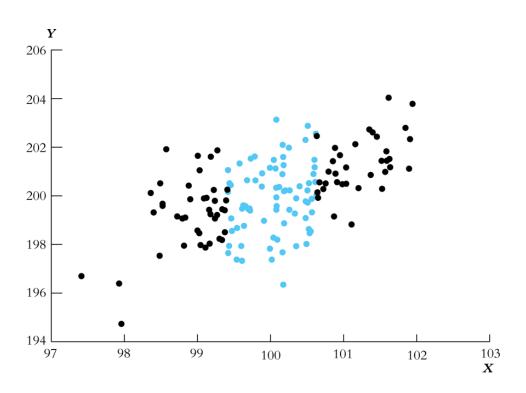
 $\beta_0 \& \beta_1$

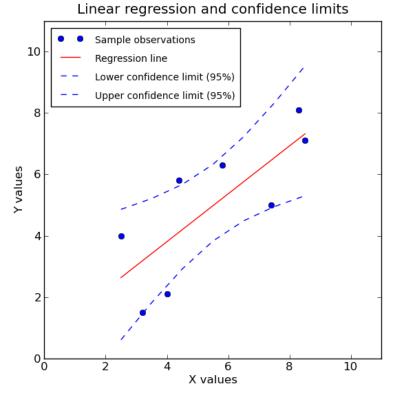
OLS estimator from sample data:

$$Y_i = (\hat{\beta}_0) + (\hat{\beta}_1) X_i + \hat{u}_i$$

- $\hat{\beta}_1$ estimates a causal effect of X on Y only if $corr(X_i, u_i) = 0$.
 - No confounding factors affecting both X & Y, and no reverse causality Y->X.
 - (...and sample is random, and outliers are rare)

2. Statistical inference about linear regression Linear regression and confidence limits





Quant methods

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Inference about linear regression

• Test hypotheses about population coefficients β_0 & β_1 .

- Build confidence intervals about β_0 & β_1 .
 - A range of values with (say) 95% probability of including true coefficients.

Hypothesis tests

Null and alternative hypotheses:

$$H_0: \beta_1 = \beta_{1,0} \text{ vs. } H_1: \beta_1 \neq \beta_{1,0}$$

- Three steps for testing H_0 :
- 1. Compute $\hat{\beta}_1$ and $SE(\hat{\beta}_1)$ using sample data.
- 2. Compute the t-statistics
- 3. Compute the p-value

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The standard error of $\hat{\beta}_1$

• $SE(\hat{\beta}_1)$ is an estimator of $\sigma_{\hat{\beta}_1}$.

•
$$SE(\hat{\beta}_1) = \sqrt{\hat{\sigma}_{\hat{\beta}_1}^2} = \frac{1}{n} \times \frac{\frac{1}{n-2} \sum_{i=1}^n (X_i - \bar{X})^2 \hat{u}_i^2}{\left[\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2\right]^2}$$

- (complicated, but STATA will do it for you)
- Also called robust standard error.
- To obtain this type of SE in STATA, you use the 'robust' option.

```
regress testscr str, robust
Regression with robust standard errors
                                                 Number of obs = 420
                                                 F(1, 418) = 19.26
Prob > F = 0.0000
                              Standard error for
 Standard error for
                                                 R-squared = 0.0512
                              intercept SE(\hat{\beta}_0)
 slope SE(\hat{\beta}_1)
                                                 Root MSE = 18.581
                       Robust
              Coef
                      Std. Err.
                                          P>|t| [95% Conf. Interval]
testscr |
                       .5194892
                                          0.000 \quad -3.300945 \quad -1.258671
          -2.279808
                                   4.39
    str |
           698.933
                       10.36436
                                  67.44
                                          0.000 678.5602 719.3057
```

•
$$\hat{\beta}_1 = -2.28$$
 and $SE(\hat{\beta}_1) = 0.52$

•
$$\hat{\beta}_0 = 698.9$$
 and $SE(\hat{\beta}_1) = 10.36$

HYPOTHESIS TESTS

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t-statistics for OLS estimated coefficients

$$t = \frac{estimated\ coeff. -hypothesized\ value}{standard\ error\ of\ estimator}$$

$$t = \frac{\hat{\beta}_1 - \hat{\beta}_{1,0}}{SE(\hat{\beta}_1)}$$

- t has a standard normal distribution in large samples
- $t \sim N(0,1)$

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Regression with robust standard errors
                                    Number of obs = 420
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                                t-stat for Prob > F = 0.0000
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 H_0: \beta_1 = 0
                                            Root MSE = 18.581
                     Robust
                    Std. Err.
testscr |
             Coef.
                                      P>|t| [95% Conf. Interval]
                               -4.39
         -2.279808 .5194892
                                      0.000
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   str |
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                   10.36436
                                      0.000
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```

•
$$\hat{\beta}_1 = -2.28$$
 and $SE(\hat{\beta}_1) = 0.52$ and $t = -4.39$

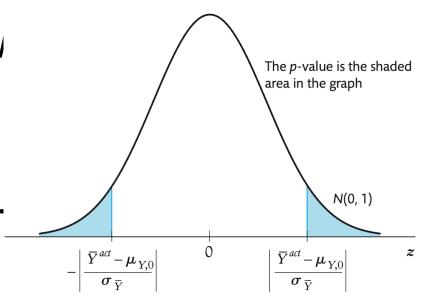
•
$$\hat{\beta}_0 = 698.9$$
 and $SE(\hat{\beta}_1) = 10.36$ and $t = 67.44$

Hypothesis tests

Null and alternative hypotheses:

$$H_0: \beta_1 = \beta_{1,0} \text{ vs. } H_1: \beta_1 \neq \beta_1$$

- Three steps for testing H_0 :
- 1. Compute $\hat{\beta}_1$ and $SE(\hat{\beta}_1)$ using sample data.
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- 3. Compute the p-value



Computing the p-value

• p-value =
$$Pr_{H_0}[|\hat{\beta}_1 - \beta_{1,0}| > |\hat{\beta}_1^{act} - \hat{\beta}_{1,0}|]$$

"Probability under the null hypothesis...

...that the difference between the estimated coefficient and the null hypothesis... ...is at least as large as the one we obtained in our sample."

$$=2\phi(-|t^{act}|)$$

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                                     0.000
                                               678.5602 719.3057
                              67.44
```

- $\hat{\beta}_1 = -2.28$ and $SE(\hat{\beta}_1) = 0.52$ and t = -4.39 and p < 0.001
- $\hat{\beta}_0 = 698.9$ and $SE(\hat{\beta}_1) = 10.36$ and t = 67.44 and p < 0.001

Confidence interval for β_1

- 95% confidence interval: a range of values that is 95% likely to include the "true" population coefficient $m{\beta_1}$.
- The set of β_1 values that we *cannot* reject at the 5% significance level.
- 95% confidence interval for β_1 :

$$\hat{\beta}_1 - 1.96 * SE(\hat{\beta}_1) \le \beta_1 \le \hat{\beta}_1 + 1.96 * SE(\hat{\beta}_1)$$

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                                                  -1.258671
 cons | 698.933 10.36436 67.44 0.000
                                         678.5602 719.3057
```

• Confidence interval for β_1 : [-3.30 $\leq \beta_1 \leq$ -1.26]

Confidence interval for predicted effects

• Confidence interval for the effect of a Δx change in X:

$$\left[(\hat{\beta}_1 \ lower \ bound) \times \Delta x ; (\hat{\beta}_1 \ upper \ bound) \times \Delta x \right]$$

$$\left[(\hat{\beta}_1 - 1.96 * SE(\hat{\beta}_1)) \times \Delta x ; \hat{\beta}_1 + 1.96 * SE(\hat{\beta}_1) \times \Delta x \right]$$

Example: Confidence interval for the average effect of a 3.5 increase in STR

• Confidence interval for β_1 (coefficient of STR):

$$[-3.30 \le \beta_1 \le -1.26]$$

- Confidence interval for 3.5 increase in STR:
 - \circ Lower bound: -3.30 * 3.5 = -11.55
 - \circ Upper bound: -1.26 * 3.5 = -4.41
- An increase in STR by 3.5 students is associated with a decrease in test scores between 4.41 and 11.55 points.

$$[-11.55 \le \beta_1 \le -4.41]$$

Regression with binary regressor

- Binary (or indicator or dummy) variables
 - Sex at birth (1 = female; 0 = male)
 - Urban or rural (1 = urban; 0 = rural)
 - Treatment or placebo(1 = treatment; 0 = placebo)
 - O



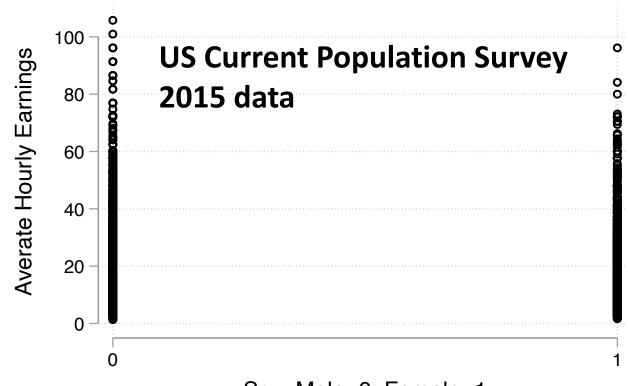
Example: the gender pay gap

Y = Average Hourly Earnings (AHE)

D = Sex at birth (Female)

$$Y_i = \beta_0 + \beta_1 D_i + u_i$$

How do we interpret β_1 ?



Sex, Male=0; Female=1

in STATA: scatter ahe female

Regression with binary regressor

$$E(Y|D) = \beta_0 + \beta_1 D$$

$$Y_i = \beta_0 + \beta_1 D_i + u_i$$

For a male worker ($D_i = 0$):

$$E(Y|D=0) = \beta_0 + \beta_1 \times 0 = \beta_0$$

For a female worker ($D_i = 1$):

$$E(Y|D=1) = \beta_0 + \beta_1 \times 1 = \beta_0 + \beta_1$$



$$\beta_1 = E(Y|D=1) - E(Y|D=0)$$

Regression with binary regressor

$$Y_i = \beta_0 + \beta_1 D_i + u_i$$

- $\hat{\beta}_0$ = sample mean of Y when D=0
- $\hat{\beta}_0 + \hat{\beta}_1 = \text{sample mean of Y when D=1}$
- $\hat{\beta}_1$ = difference in group means
- T-stats, p-value, confidence intervals calculated as usual.
- Will give the same result as a t-test for difference in means.

Example: the gender pay gap

. reg ahe female, robust

Linear regression

• AHE for men (D=0):

$$\hat{\beta}_0 = 18.33$$

 Difference between women and men:

$$\hat{\beta}_1 = -2.50$$

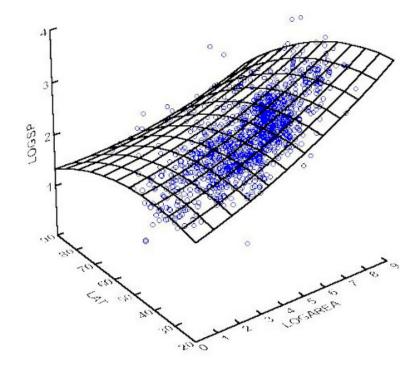
ahe	Coefficient	Robust std. err.	t	P> t	[95% conf.	interval]
female	-2.495648	.1835205	-13.60	0.000	-2.855375	-2.135922
_cons	18.32845		140.91	0.000	18.0735	18.5834

• AHE for women (D=1):

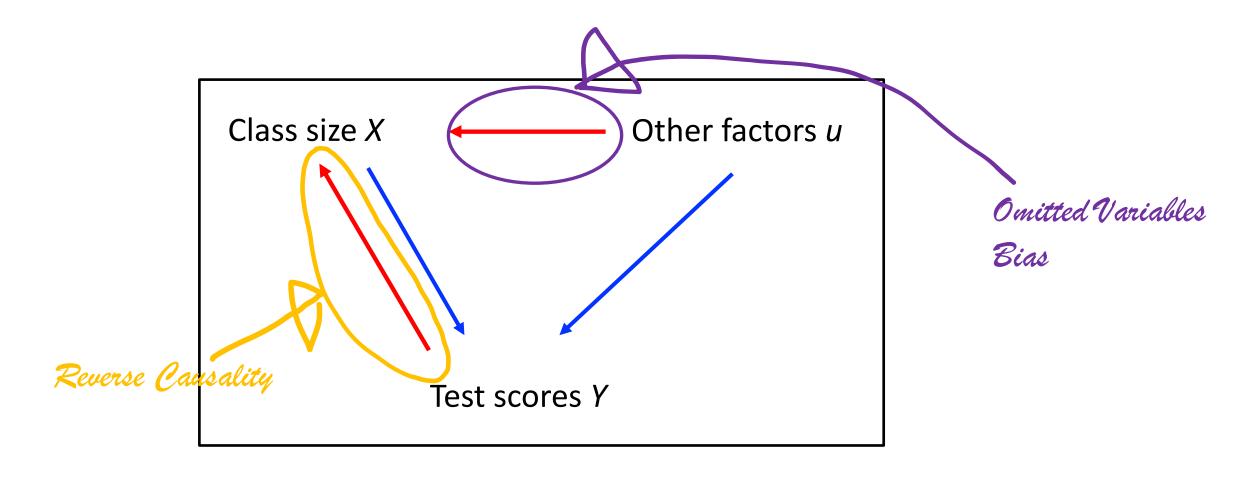
$$\hat{\beta}_0 + \hat{\beta}_1 =$$
= 18.32 - 2.50 = 15.83

(US Current Population Survey 2015 data)

3. Linear regression with multiple regressors



CAUSAL RELATIONS BETWEEN CLASS SIZE & TEST SCORES



Omitted variables bias

Omitted Variables Bias (OVB) occurs if:

1. The omitted variable is correlated with the included regressor X.

AND

2. The omitted variable affects the dependent variable Y.





Thank you for your attention