## AFRE 802 Statistical Methods for Agricultural, Food, & Resource Economists



Linear models & estimation by least squares – Part 3 of 3 (WMS Ch. 11.5 & Wooldridge pp. 113-136)

December 5, 2017

Nicole Mason Michigan State University Fall 2017

### **GAME PLAN**

- Housekeeping issues:
  - · Office hours this week are Wednesday, 11 AM-1 PM
  - · Friday optional review session this week will be 4-5 PM
  - I will hold extra office hours next Tuesday (Dec. 12) from 3-5 PM in the Cook Hall basement
- Return take-home graded exercise (see answer key in 2014 final exam on D2L)
- Collect Thursday's additional practice problem
- · Distribute new additional practice problem
- Review

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- Linear models & estimation by least squares Part 3 of 3
  - · Classical linear model assumptions
  - Inference
    - Hypothesis testing & p-values
    - · Confidence intervals

Review: Total, explained, & residual SS, R<sup>2</sup>

Total sum of squares: 
$$SST \equiv \sum_{i=1}^{N} (y_i - \overline{y})^2$$

**Explained sum of squares:**  $\left| SSE \equiv \sum_{i=1}^{N} (\hat{y}_i - \overline{y})^2 \right|$ 

$$SSE = \sum_{i=1}^{N} (\hat{y}_i - \overline{y})^2$$

**R**esidual sum of squares:  $SSR = \sum_{i=1}^{N} \hat{u}_{i}^{2}$ 

$$SSR \equiv \sum_{i=1}^{N} \hat{u}_i^2$$

$$SST = SSE + SSR$$

Coefficient of determination or 
$$R^2$$
: Interpretation? The proportion of the sample variation in  $y$  that is explained by  $x$ 

Review: Simple linear regression assumptions & implications

SLR.1-SLR.4 → OLS estimators unbiased

**SLR.1.** Linear in parameters:

SLR.2. Random sampling

\*\*SLR.3. Zero conditional mean (exogeneity):

$$E(u \mid x) = E(u) = 0$$

SLR.4. Sample variation in x

SLR.5. Homoskedasticity (constant variance):

$$V(u \mid x) = V(u) = \sigma^2$$

→ Formulas for variances of OLS estimators are:

$$V(\hat{\beta}_{1}) = \frac{\sigma^{2}}{\sum_{i=1}^{N} (x_{i} - \overline{x})^{2}} V(\hat{\beta}_{0}) = \frac{\sigma^{2} N^{-1} \sum_{i=1}^{N} x_{i}^{2}}{\sum_{i=1}^{N} (x_{i} - \overline{x})^{2}}$$

→ SLR.1-SLR.5 → OLS is **BLUE** (Gauss-Markov Theorem)

Unbiased & consistent estimator of  $V(u) = \sigma^2$ 

$$\hat{\sigma}^2 = \frac{1}{N - 2} \sum_{i=1}^{N} \hat{u}_i^2 = \frac{SSR}{N - 2}$$

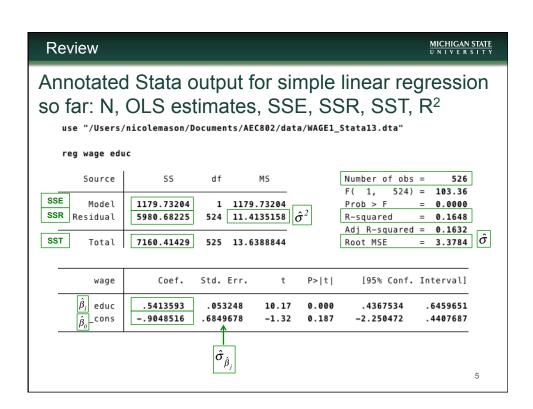
Use in formulas to estimate variances and obtain standard errors of our OLS estimators:

$$\hat{V}(\hat{\beta}_{I}) = \frac{\hat{\sigma}^{2}}{\sum_{i=1}^{N} (x_{i} - \overline{x})^{2}}$$

$$\hat{V}(\hat{\beta}_{I}) = \frac{\hat{\sigma}^{2}}{\sum_{i=I}^{N} (x_{i} - \overline{x})^{2}} \qquad \hat{V}(\hat{\beta}_{0}) = \frac{\hat{\sigma}^{2} N^{-I} \sum_{i=I}^{N} x_{i}^{2}}{\sum_{i=I}^{N} (x_{i} - \overline{x})^{2}}$$

$$\hat{\sigma}_{\hat{\beta}_{j}} = \sqrt{\hat{V}(\hat{\beta}_{j})} \text{ for } j = 0, I$$

$$\hat{\sigma}_{\hat{\beta}_j} = \sqrt{\hat{V}(\hat{\beta}_j)} \text{ for } j = 0, 1$$



What we know about the sampling distributions of the OLS estimators so far

$$y = \beta_0 + \beta_1 x + u$$

**OLS** estimators for  $\beta_0$  and  $\beta_1$ :

$$\hat{\beta}_{I} = \frac{\sum_{i=1}^{N} (x_{i} - \overline{x})(y_{i} - \overline{y})}{\sum_{i=1}^{N} (x_{i} - \overline{x})^{2}} \hat{\beta}_{0} = \overline{y} - \hat{\beta}_{I} \overline{x}$$

**Expected values** (under SLR.1-SLR.4):

$$E(\hat{\boldsymbol{\beta}}_I) = \boldsymbol{\beta}_I \text{ and } E(\hat{\boldsymbol{\beta}}_0) = \boldsymbol{\beta}_0$$

Sample variances (under SLR.1-SLR.5):

$$\hat{V}(\hat{\beta}_I) = \frac{\hat{\sigma}^2}{\sum_{i=1}^{N} (x_i - \overline{x})^2}$$

$$\hat{V}(\hat{\beta}_{I}) = \frac{\hat{\sigma}^{2}}{\sum_{i=1}^{N} (x_{i} - \overline{x})^{2}} \hat{V}(\hat{\beta}_{0}) = \frac{\hat{\sigma}^{2} N^{-I} \sum_{i=1}^{N} x_{i}^{2}}{\sum_{i=1}^{N} (x_{i} - \overline{x})^{2}}$$
where  $\hat{\sigma}^{2} = \frac{I}{N-2} \sum_{i=1}^{N} \hat{u}_{i}^{2} = \frac{SSR}{N-2}$ 

$$\hat{\sigma} \text{ is the standard error}$$
of the regression

where 
$$\hat{\sigma}^2 = \frac{1}{N-2} \sum_{i=1}^{N} \hat{u}_i^2 = \frac{SSR}{N-2}$$

of the regression

### The sampling distributions of the OLS estimators

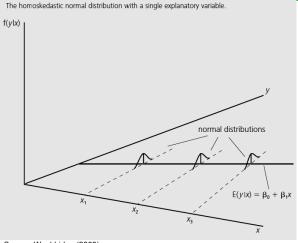
- By CLT, Under assumptions SLR.1-SLR.5, the OLS estimators are **asymptotically** (i.e., as  $N \rightarrow \infty$ ) **normally distributed** with the means & variances on the previous slides
- If we add one more assumption, then we can obtain the sampling distribution of the OLS estimators in finite samples

**SLR.6.** Normality: The population error, *u*, is independent of x and is normally distributed with E(u)=0 and  $V(u)=\sigma^2$ , i.e.:

 $u \sim Normal(0, \sigma^2)$ 

SLR.1-SLR.6 = "classical linear model assumptions"

- CLM = Gauss-Markov + SLR.6 (normality)
- CLM assumptions imply  $y \mid x \sim Normal(\beta_0 + \beta_I x, \sigma^2)$



Source: Wooldridge (2003)

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$$y = \beta_0 + \beta_1 x + u$$

The sampling distributions of the OLS estimators under the CLM assumptions (SLR.1-SLR.6):

$$\hat{\boldsymbol{\beta}}_{j} \sim Normal\left(\boldsymbol{\beta}_{j}, V(\hat{\boldsymbol{\beta}}_{j})\right) \quad \text{where } V(\hat{\boldsymbol{\beta}}_{l}) = \frac{\sigma^{2}}{\sum\limits_{i=1}^{N} (x_{i} - \overline{x})^{2}}, \\
V(\hat{\boldsymbol{\beta}}_{0}) = \frac{\sigma^{2} N^{-l} \sum\limits_{i=1}^{N} x_{i}^{2}}{\sum\limits_{i=1}^{N} (x_{i} - \overline{x})^{2}} \qquad \hat{\sigma}^{2} = \frac{1}{N-2} \sum\limits_{i=1}^{N} \hat{u}_{i}^{2} = \frac{SSR}{N-2}$$

If we **know**  $\sigma^2$ , then we can standardize beta-hat<sub>j</sub> to a **Z-statistic**; otherwise, we can **estimate**  $\sigma^2$  and compute a **T-statistic** – i.e.:

$$Z = \frac{\hat{\beta}_{j} - \beta_{j}}{\sqrt{V(\hat{\beta}_{j})}} \sim Normal(0, 1)$$

$$T = \frac{\hat{\beta}_{j} - \beta_{j}}{\sqrt{\hat{V}(\hat{\beta}_{j})}} \sim t \text{ with } N - 2 \text{ d.f.}$$

$$\hat{\sigma}_{\hat{\beta}_{j}} = \frac{\hat{\beta}_{j} - \beta_{j}}{\sqrt{\hat{V}(\hat{\beta}_{j})}} \sim t \text{ with } N - 2 \text{ d.f.}$$

# Testing hypotheses about $\beta_0$ or $\beta_1$ $y = \beta_0 + \beta_1 x + u$

- 1. State the <u>null & alternative hypotheses</u>: e.g.,  $H_0: \beta_i = 0, H_I: \beta_i \neq 0$
- 2. Define an appropriate <u>test statistic</u>:  $\hat{\beta}_i$
- 3. Determine the distribution of the test statistic under the null hypothesis  $\hat{\boldsymbol{\beta}}_{i} \sim Normal(0, V(\hat{\boldsymbol{\beta}}_{i}))$
- 4. Standardize the test statistic to something with known/tabled probabilities for its sampling distribution (e.g., Z, t, chi-square, F)

$$Z = \frac{\hat{\beta}_{j} - 0}{\sigma_{\hat{\beta}_{j}}} \sim Normal(0, 1)$$

$$Z = \frac{\hat{\beta}_j - 0}{\sigma_{\hat{\beta}_j}} \sim Normal(0, 1)$$

$$T = \frac{\hat{\beta}_j - 0}{\hat{\sigma}_{\hat{\beta}_j}} \sim t \text{ with } N - 2 \text{ d.f.}$$

- 5. Choose a <u>significance level</u> ( $\alpha$ , the P(Type | error) = P(reject thenull when it is true), typically 0.01, 0.05, or 0.10) & a rejection **region OR** compute the **p-value** for the test statistic.
- 6. Reject the null hypothesis if the standardized statistic lies in the rejection region (or if p-value≤α); fail to reject otherwise

# Example #1: Testing hypotheses about $\beta_0$ or $\beta_1$

reg bwght cigs

Source	SS	df	MS
Model Residual	13060.4194 561551.3	1 1386	13060.4194 405.159668
Total	574611.72	1387	414.283864

Number of obs	=	1388
F( 1, 1386)	=	32.24
Prob > F	=	0.0000
R-squared	=	0.0227
Adj R-squared	=	0.0220
Root MSE	=	20.129

bwght	Coef.	Std. Err.
cigs	5137721	.0904909
_cons	119.7719	.5723407

*Test the following hypotheses at the a* = 0.05 *level. Also find the p-values.* 

$$H_0: \beta_{cigs} = 0 \text{ vs. } H_1: \beta_{cigs} \neq 0$$
  
and  
 $H_0: \beta_{cigs} = 0 \text{ vs. } H_1: \beta_{cigs} < 0$ 

$$T = \frac{\hat{\beta}_j - 0}{\hat{\sigma}_{\hat{\beta}_j}} \sim t \text{ with } N - 2 \text{ d.f.}$$

## T-stats and p-values in Stata output

#### . reg bwght cigs

Source	SS	df	MS
Model Residual	13060.4194 561551.3	1 1386	13060.4194 405.159668
Total	574611.72	1387	414.283864

=	1388
=	32.24
=	0.000
=	0.022
=	0.022
=	20.129
	= = =

bwght	Coef.	Std. Err.	t	P> t
cigs	5137721	.0904909	-5.68	0.000
_cons	119.7719	.5723407	209.27	0.000

The p-values reported by Stata are for  $H_0: \beta_j = 0$  vs.  $H_1: \beta_j \neq 0$ 

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# Example #2: Testing hypotheses about $\beta_0$ or $\beta_1$

$$\log(crime) = \beta_0 + \beta_1 \log(enroll) + u$$

$$\log(\hat{c}rime) = -6.63 + 1.27 \log(enroll)$$

$$(1.03) \quad (0.11)$$

$$n = 97, R^2 = .585.$$

Aside on interpreting results in log-log models

*crime* is the annual number of crimes on college campuses and *enroll* is student enrollment. The numbers in parentheses are standard errors.

Use the regression output above to test the following hypotheses at the  $\alpha$ =0.05 level. Also find the associated p-values.

$$\begin{aligned} & H_0: \beta_I = 1 \quad \text{vs.} \quad H_I: \beta_I \neq 1 \\ & \text{and} \\ & H_0: \beta_I = 1 \quad \text{vs.} \quad H_I: \beta_I > 1 \end{aligned}$$

Summary of Functional Forms Involving Logarithms

$$y = \beta_0 + \beta_1 x + u$$

Model	Dependent Variable	Independent Variable	Interpretation of $oldsymbol{eta}_1$
level-level	у	$X \qquad \beta_I = \frac{\Delta}{\Delta}$	$\Delta y = \beta_1 \Delta x$
level-log	у	102111 ====	$\frac{\Delta y}{\Delta x} \Delta y = (\beta_1/100)\% \Delta x$
log-level	$\log(y)$	$X = 100\beta_1 = -$	$\frac{\%\Delta y}{\Delta x} \% \Delta y = (100\beta_1) \Delta x$
log-log	$\log(y)$	$ \log(x)   B_i = -$	$\frac{\partial \Delta y}{\partial \Delta x}  \% \Delta y = \beta_1 \% \Delta x$

Source: Wooldridge (2003)

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# Confidence intervals for $\beta_0$ or $\beta_1$

### Recall from earlier in the course:

Two-sided, large-sample (1- $\alpha$ )% confidence interval for  $\theta$ :  $\hat{\theta} \pm z_{\alpha/2}\sigma_{\hat{\theta}}$  Two-sided, small-sample (1- $\alpha$ )% confidence interval for  $\mu$ :  $\overline{Y} \pm t_{\alpha/2}\hat{\sigma}_{\overline{Y}}$ ,

 $(N-1 \text{ d.f. for } t_{\alpha/2})$ 

Two-sided, finite sample (1- $\alpha$ )% confidence interval for  $\beta_j$  (in the case of simple linear regression):

$$\hat{\beta}_{j} \pm t_{\alpha/2} \hat{\sigma}_{\hat{\beta}_{j}}$$

$$(N-2 \text{ d.f. for } t_{\alpha/2})$$

#### MICHIGAN STATE Example #1: Confidence intervals for $\beta_0$ or $\beta_1$ reg bwght cigs SS Number of obs =Source d f MS F(1, 1386) = 32.24Model 13060.4194 1 13060.4194 Prob > F Residual 561551.3 1386 405.159668 R-squared = 0.0227 Adj R-squared = 0.0220 574611.72 1387 414.283864 Total Root MSE 20.129 bwght Coef. Std. Err. P>|t| $\hat{\beta}_{j} \pm t_{\alpha/2} \hat{\sigma}_{\hat{\beta}_{i}}$ -.5137721 -5.68 0.000 cigs .0904909 $(N-2 \text{ d.f. for } t_{\alpha/2})$ 119.7719 .5723407 209.27 0.000 \_cons a. Find the 95% (two-sided) confidence interval for $\beta_{cigs}$ . Relate this to $H_0$ : $\beta_{cigs} = 0$ vs. $H_1$ : $\beta_{cigs} \neq 0$ at $\alpha = 0.05$ . b. Find the 95% upper confidence interval for $\beta_{cigs}$ . Relate this $\overline{\text{to } H_0}$ : $\beta_{cigs} = 0$ vs. $H_1$ : $\beta_{cigs} < 0$ at $\alpha = 0.05$ .

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## 95% confidence intervals in Stata output

### reg bwght cigs

Source	SS	df	MS
Model Residual	13060.4194 561551.3	1 1386	13060.4194 405.159668
Total	574611.72	1387	414.283864

Number of obs = 1388 F( 1, 1386) = 32.24 Prob > F = 0.0000 R-squared = 0.0227 Adj R-squared = 0.0220 Root MSE = 20.129

bwght	Coef.	Std. Err.	t	P> t	[95% Conf.	. Interval]
cigs _cons		.0904909 .5723407			6912861 118.6492	3362581 120.8946

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# Example #2: Confidence intervals for $\beta_0$ or $\beta_1$

$$\log(crime) = \beta_0 + \beta_1 \log(enroll) + u$$

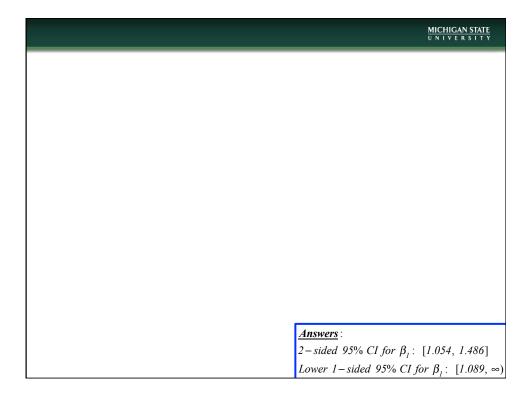
$$\log(\hat{c}rime) = -6.63 + 1.27 \log(enroll)$$
  
(1.03) (0.11)  
 $n = 97, R^2 = .585.$ 

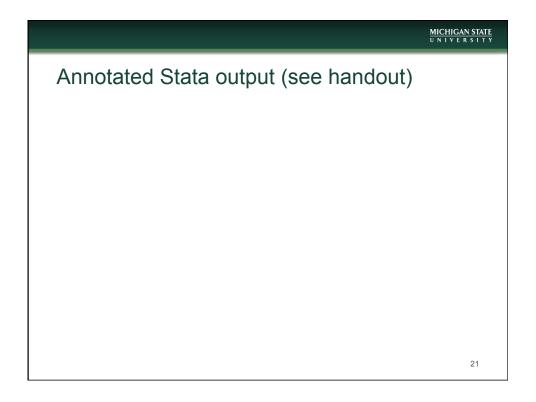
*crime* is the annual number of crimes on college campuses and *enroll* is student enrollment. The numbers in parentheses are standard errors.

a. Find the 95% (two-sided) confidence interval for  $\beta_1$ . Relate this to  $H_0$ :  $\beta_1$  =1 vs.  $H_1$ :  $\beta_1 \sim$ = 1 at  $\alpha$ =0.05. b. Find the 95% <u>lower</u> confidence interval for  $\beta_1$ . Relate this to  $H_0$ :  $\beta_1$  =1 vs.  $H_1$ :  $\beta_1 > 1$  at  $\alpha$ =0.05.

$$\hat{\beta}_{j} \pm t_{\alpha/2} \hat{\sigma}_{\hat{\beta}_{j}}$$

$$(N-2 \text{ d.f. for } t_{\alpha/2})$$





### Homework: Ch. 11 (cont'd)

- 1. Finish the other parts of Thursday's HW
- 2. Using the data in WMS 11.3, test  $H_0$ :  $\beta_1$  =0 vs.  $H_1$ :  $\beta_1 \sim$ = 0, and  $H_0$ :  $\beta_1$  =0 vs.  $H_1$ :  $\beta_1 <$  0, both at the at  $\alpha$ =0.05 level. Also find the 95% two-sided and upper CIs, and relate the results to your hypothesis tests above.
- 3. Using the data in tourism.dta (on D2L) and Stata, regress household tourism expenditure (*tourismexp*) on household income (*income*). Interpret the estimate for  $\beta_1$ , and construct 99% two-sided and lower CIs for  $\beta_1$ . Use the CI results to test H<sub>0</sub>:  $\beta_1$ =0.05 vs. H<sub>1</sub>:  $\beta_1$ ~= 0.05, and H:  $\beta_1$ =0.05 vs. H<sub>1</sub>:  $\beta_1$ >0.05 at  $\alpha$ =0.01 level.
- Please try to complete all Ch. 11 HW before class on Thursday so that we can go over it then (you won't turn in Ch. 11)

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### Game plan for Thursday (last day of class)

- Finish any material on today's slides that we didn't get to
- Go over answers to additional practice problem
- Go over any questions you have on the Ch. 11 HW, past final exams, or other HWs/course material

### Final exam details

- · Cumulative but with emphasis on Ch. 7-Ch. 11
- Please bring paper, pencil, calculator, and cheat sheets (two 8.5x11" sheets, front and back). Please write last 4 digits of your PID on paper in advance to save time.
- Exam is closed book/notes except for cheat sheets
- Exam is in this room from 12:45-2:45 PM (hard stop) next Thursday, December 14