## Lecture 2: Econometrics Primer

This lecture is very terse review of econometrics from ECON 141: Introduction to Econometrics. We will not cover this material in class, but this outline is designed to help guide you with reading the Studenmund chapters assigned as background reading.

- I. What is econometrics?
  - Measurement quantitative measurement of economic phenomena
  - Uses
    - Describe/quantify economic reality
    - Testing hypotheses of economic theory
    - Forecasting future economic activity
  - Explain/quantify the behavior of dependent variable using explanatory variables.
- II. Fundamentals
  - A. Correlation vs. causation
    - Empirically, we can only quantify relationships in terms of correlation
    - Causation is based on our underlying model.
    - <u>Example</u>: Relationship between real GDP, capital, and labor.
       Empirically, we can see how these variables are related
       We assume a causal relationship based on the production function we assume capital and labor are determined exogenously.
  - B. Single-equation linear model
    - 1) Variables
      - X explanatory variable (independent variable)
      - Y dependent variable
    - 2) Function
      - Theoretical model:  $Y = \beta_0 + \beta_1 X$
      - Data:  $Y = \beta_0 + \beta_1 X + e$
    - 3) Residual, e
      - 1. Specification error:
        - a. Influences omitted from the equation
        - b. Nonlinear relationship
      - 2. Measurement error
      - 3. Unpredictable variation
  - C. Cross section vs. time series data
    - 1) Notation
      - common to use "i" to denote cross section (for individual)
        - common to use "t" to denote time series (time interval)
    - 2) Example: Consumption Function
      - $C = \beta_0 + \beta_1 DI$
      - Cross section data on individual household consumption and household disposable income
      - Time series data on aggregate consumption and disposable income

#### D. Estimated relationship

- 1) Predicted value of  $Y :: Yhat = E(Y_i | X_i)$
- 2) Estimated value of e :: ehat = Yhat Y
- III. OLS

A. Overview

1) Objective

1. Summation Notation

Minimize the sum of squared errors

Choose  $\beta_0$  and  $\beta_1$  to minimize the sum of squared residuals:

$$\min \sum_{i=1}^{N} (e_i)^2 = \min \sum_{i=1}^{N} (Y_i - \beta_o - \beta_1 X_i)^2$$

First-order conditions:

$$\frac{\partial}{\partial \beta_0} = 0 : -2 \Big[ \sum Y_i - N\beta_0 - \beta_1 \sum X_i \Big] = 0$$
$$\Rightarrow \beta_0 = \frac{\sum Y_i}{N} - \beta_1 \frac{\sum X_i}{N}$$
$$\Rightarrow \beta_0 = \overline{Y} - \beta_1 \overline{X}$$

$$\frac{\partial}{\partial \beta_{1}} = 0 : -2 \Big[ \sum (Y_{i} - \beta_{0} - \beta_{1} X_{i}) \sum X_{i} \Big] = 0$$
  

$$\Rightarrow \Big[ \sum (Y_{i} - (\overline{Y} - \beta_{1} \overline{X}) - \beta_{1} X_{i}) \sum X_{i} \Big] = 0$$
  

$$\Rightarrow \sum \Big[ (Y_{i} - \overline{Y}) (X_{i} - \overline{X}) \Big] - \beta_{1} \sum (X_{i} - \overline{X})^{2} = 0$$
  

$$\beta_{1} = \frac{\sum \Big[ (Y_{i} - \overline{Y}) (X_{i} - \overline{X}) \Big]}{\sum (X_{i} - \overline{X})^{2}}$$

2. Matrix Notation  $Y = X\beta + e$ where Y is an n x 1 vector e is an n x 1 vector X is an n x k matrix  $\beta$  is a k x 1 vector

 $\min(e'e) = \min(Y - X\beta)'(Y - X\beta) = \min(Y'Y - 2\beta X'Y + \beta X'X\beta)$  $\frac{\partial}{\partial \beta} = 0: -2X'Y + 2X'X\beta = 0$  $\Rightarrow (X'X)\beta = X'Y$  $\Rightarrow \beta = (X'X)^{-1}X'Y$ 

- B. Features
  - 1) Ybar = b0 + b1Xbar
  - 2) Sum(e)=0
    - 3) OLS is BLUE
- C. Evaluating the regresion
  - 1) R<sup>2</sup>
  - 2) F-test
  - 3) T-test of individual coefficients

# IV. CLM

A. Assumptions (let T =sample size)

- Linear and correctly specified
  - E(e)=0
  - E(X,e)=0
  - E(e<sub>t</sub>,e<sub>t-s</sub>)=0 no autocorrelation
  - E(e<sup>2</sup>)=σ<sup>2</sup> no heteroskedasticity
  - No perfect correlation
  - e ~ N(0,σ<sup>2</sup>)
- B. OLS is BLUE Gauss Markov Theorem implies the following for the estimated  $\beta$ :
  - Unbiased:

- $E[\beta hat] = \beta$
- Minimum variance (efficient)
- var[ $\beta$ hat] is as small as possible lim E[ $\beta$ hat]  $\rightarrow \beta$  as T $\rightarrow \infty$
- ConsistentNormal distribution
- $\beta$ hat ~ N( $\beta$ ,var( $\beta$ hat))

V. Hypothesis Testing

# A. Overview

- It's almost never possible to prove something (theory) correct or "true" in the same way we can in mathematics.
- Strategy: Take a random sample to see whether it conforms to a hypothesis
  - If we can reject a hypothesis with a certain degree of confidence, then it's very unlikely the sample result would have been observed if the theory were correct.

### B. Steps

- 1) Set up null and alternative hypothesis
  - H<sub>0</sub>:  $\beta_1 = 0$

 $H_{\alpha}: \beta_1 = 0$ 

Analogy: guilt or innocence of the accused

 Determine degree of confidence w/ which to reject the null Type I error: reject a true null hypothesis = find an innocent person guilty Type II error: fail to reject a false null = find the guilty person innocent

We face a tradeoff, which type of error do we want to avoid?

Eliminate Type I error – never reject the null = find everyone innocent Reject the null only when we're very confident

3) Decision rule

Common decision rule is to use a 95% confidence level – 90% and 99% also common

### C. t-test

Used for hypothesis testing of individual regression coefficients Standardize the  $\beta$ hat to use a common distribution – the t-distribution.

In the CLM,  $\beta$ hat ~ N( $\beta$ ,var( $\beta$ hat)).

 $t = (\beta hat - \beta_0)/se(\beta hat)$   $t \sim N(0, s2)$ 

This is why the assumptions of the CLM are so important. If we violate any of the assumptions, like normality, no autocorrelation, no heteroskedasiticity, then the  $se(\beta hat)$  are incorrectly estimated using OLS and all of our statistical inference is incorrect.

D. F-test

Used for hypothesis testing of multiple regression coefficients at once.