Econometrics Cheat Sheet

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Data & Causality

Basics about data types and causality.

Types of data

Experimental	Data from randomized experiment
Observational	Data collected passively
Cross-sectional	Multiple units, one point in time
Time series	Single unit, multiple points in time
Longitudinal (or Panel)	Multiple units followed over multiple time periods

Experimental data

- Correlation $\Longrightarrow$ Causality
- Very rare in Social Sciences

Statistics basics

We examine a **random sample** of data to learn about the population

Random sample	Representative of population
Parameter (θ)	Some number describing population
Estimator of θ	Rule assigning value of θ to sample e.g. Sample average, $\overline{Y} = \frac{1}{N}\sum_{i=1}^{N} Y_i$
Estimate of θ	What the estimator spits out for a particular sample ($\hat{\theta}$)
Sampling distribution	Distribution of estimates across all possible samples
Bias of estimator W	$E(W) - \theta$
Efficiency	W efficient if $Var(W) < Var(\widetilde{W})$
Consistency	W consistent if $\hat{\theta} \to \theta$ as $N \to \infty$

Hypothesis testing

The way we answer yes/no questions about our population using a sample of data. e.g. "Does increasing public school spending increase student achievement?"

null hypothesis (H_0)	Typically, $H_0 : \theta = 0$
alt. hypothesis (H_a)	Typically, $H_0 : \theta \neq 0$
significance level (α)	Tolerance for making Type I error; (e.g. 10%, 5%, or 1%)
test statistic (T)	Some function of the sample of data
critical value (c)	Value of T such that reject H_0 if $\lvert T\rvert > c$; c depends on α; c depends on if 1- or 2-sided test
p-value	Largest α at which fail to reject H_0; reject H_0 if $p < \alpha$

Simple Regression Model

Regression is useful because we can estimate a *ceteris paribus* relationship between some variable x and our outcome y

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

We want to estimate $\hat{\beta}_1$, which gives us the effect of x on y.

OLS formulas

To estimate $\hat{\beta}_0$ and $\hat{\beta}_1$, we make two assumptions:

1. $E(u) = 0$
2. $E(u|x) = E(u)$ for all x

When these hold, we get the following formulas:

$$\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x}$$

$$\hat{\beta}_1 = \frac{\widehat{Cov}(y,x)}{\widehat{Var}(x)}$$

fitted values ($\hat{y}_i$)	$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$
residuals ($\hat{u}_i$)	$\hat{u}_i = y_i - \hat{y}_i$
Total Sum of Squares	$SST = \sum_{i=1}^{N}(y_i - \overline{y})^2$
Expl. Sum of Squares	$SSE = \sum_{i=1}^{N}(\hat{y}_i - \overline{y})^2$
Resid. Sum of Squares	$SSR = \sum_{i=1}^{N}\hat{u}_i^2$
R-squared (R^2)	$R^2 = \frac{SSE}{SST}$; "frac. of var. in y explained by x"

Algebraic properties of OLS estimates

$\sum_{i=1}^{N}\hat{u}_i = 0$ (mean & sum of residuals is zero)

$\sum_{i=1}^{N}x_i\hat{u}_i = 0$ (zero covariance bet. x and resids.)

The OLS line (SRF) always passes through $(\overline{x}, \overline{y})$

$SSE + SSR = SST$

$0 \leq R^2 \leq 1$

Interpretation and functional form

Our model is restricted to be **linear in parameters**

But not linear in x

Other functional forms can give more realistic model

Model	DV	RHS	Interpretation of β_1
Level-level	y	x	$\Delta y = \beta_1 \Delta x$
Level-log	y	$\log(x)$	$\Delta y = (\beta_1/100)\,[1\%\Delta x]$
Log-level	$\log(y)$	x	$\%\Delta y = (100\beta_1)\,\Delta x$
Log-log	$\log(y)$	$\log(x)$	$\%\Delta y = \beta_1 \%\Delta x$
Quadratic	y	$x + x^2$	$\Delta y = (\beta_1 + 2\beta_2 x)\,\Delta x$

Note: DV = dependent variable; RHS = right hand side

Multiple Regression Model

Multiple regression is more useful than simple regression because we can more plausibly estimate *ceteris paribus* relationships (i.e. $E(u|x) = E(u)$ is more plausible)

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + u$$

$\hat{\beta}_1, \ldots, \hat{\beta}_k$: **partial effect** of each of the x's on y

$$\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x}_1 - \cdots - \hat{\beta}_k \overline{x}_k$$

$$\hat{\beta}_j = \frac{\widehat{Cov}(y, \text{residualized } x_j)}{\widehat{Var}(\text{residualized } x_j)}$$

where "residualized x_j" means the residuals from OLS regression of x_j on all other x's (i.e. $x_1, \ldots, x_{j-1}, x_{j+1}, \ldots x_k$)

Gauss-Markov Assumptions

1. y is a linear function of the β's
2. y and x's are randomly sampled from population
3. No perfect multicollinearity
4. $E(u|x_1, \ldots, x_k) = E(u) = 0$ (Unconfoundedness)
5. $Var(u|x_1, \ldots, x_k) = Var(u) = \sigma^2$ (Homoskedasticity)

When (1)-(4) hold:	OLS is unbiased; i.e. $E(\hat{\beta}_j) = \beta_j$
When (1)-(5) hold:	OLS is Best Linear Unbiased Estimator

Variance of u (a.k.a. "error variance")

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

Variance and Standard Error of $\hat{\beta}_j$

$$Var(\hat{\beta}_j) = \frac{\sigma^2}{SST_j(1-R_j^2)}, \; j = 1, 2, ..., k$$

where

$$SST_j = (N-1)Var(x_j) = \sum_{i=1}^{N}(x_{ij} - \overline{x}_j)$$

$$R_j^2 = R^2 \text{ from a regression of } x_j \text{ on all other } x\text{'s}$$

Standard deviation:	$\sqrt{Var}$
Standard error:	$\sqrt{\widehat{Var}}$

$$se(\hat{\beta}_j) = \sqrt{\frac{\hat{\sigma}^2}{SST_j(1-R_j^2)}}, \; j = 1, \ldots, k$$

Classical Linear Model (CLM)

Add a 6th assumption to Gauss-Markov:

6. u is distributed $N(0, \sigma^2)$

Need this to know what the *distribution* of $\hat{\beta}_j$ is
Otherwise, can't conduct hypothesis tests about the β's

Testing Hypotheses about the β's

Under A (1)-(6), can test hypotheses about the β's

t-test for simple hypotheses

To test a simple hypothesis like

$$H_0 : \beta_j = 0$$
$$H_a : \beta_j \neq 0$$

use a t-test:

$$t = \frac{\hat{\beta}_j - 0}{se\left(\hat{\beta}_j\right)}$$

where 0 is the null hypothesized value.

Reject H_0 if $p < \alpha$ or if $|t| > c$ (See: Hypothesis testing)