

POLS/CS&SS 503:  
Advanced Quantitative Political Methodology  
**LINEAR REGRESSION ESTIMATOR**

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Jeffrey B. Arnold



# Overview

Regression Coefficient Anatomy

Linear Regression Population Model

Sampling Distribution

Estimators and mean squared error

Gauss-Markov Theorem

## Regression Coefficient Anatomy

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# Coefficients of a simple regression

$$Y_i = A + BX_i + E_i$$

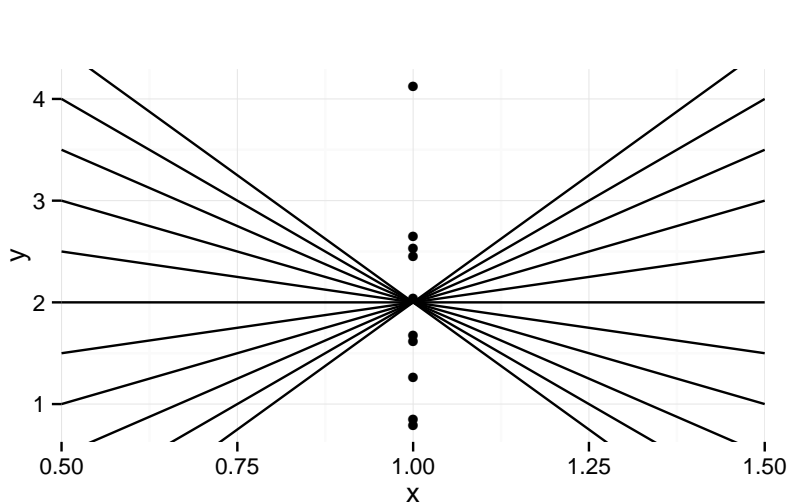
The least squares coefficients are

$$A = \bar{Y} - B\bar{X}$$

$$B = \frac{\sum_i (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_i (X_i - \bar{X})^2}$$

- State  $B$  in terms of covariance of  $X$  and  $Y$  and variance?
- State  $B$  in terms of correlation of  $X$  and  $Y$  and standard deviations?
- What values can  $B$  take if  $\text{sd}(X) = \text{sd}(Y) = 1$ ?
- What is  $\hat{Y}$  for  $X = \bar{X}$ ?
- What happens to  $B$  as  $V(X)$  decreases?  $V(Y)$  decreases? If  $V(X) = 0$

## Least squares when $V X = 0$



# Least squares coefficients are unidentified if $Vx = 0$

- If  $Vx = 0$  then least squares solution is unidentified
- There is no unique value of  $A, B$  that  $\arg \min_{A,B} \sum_i E_i^2$

```
y <- c(1, 2, 3, 4, 5)
x <- 1
ybar <- mean(y)
ybar

## [1] 3

# A = 2, B = 1
sum((y - 2 - 1 * x) ^ 2)

## [1] 10

# A = -7, B = 10
sum((y + 7 - 10 * x) ^ 2)

## [1] 10
```

# Coefficients of a multiple regression

$$\vec{Y} = Xb + e$$

- $b = (X'X)^{-1}X'y$ . *Not that intuitive!*
- Coefficient  $b_j$  is

$$b_k = \frac{C(y, \tilde{x}_j)}{V(\tilde{x}_k)}$$

- Where  $\tilde{x}_j$  are the residualls of  $x_j$  on all  $X_h$  where  $h \neq j$

$$\tilde{X}_{j,i} = X_{j,i} - \tilde{A} - \sum_{h \neq j} \tilde{B}_h X_h$$

# Regression example

See `multiple_regression_anatomy.R`



# Least Squares coefficients are unidentified if $(X'X)^{-1}$ does not exist

- Common cases in which  $(X'X)^{-1}$  does not exist:
  - Number of observations less than  $k + 1$
  - $X_k$  is constant
  - $X_k$  is a linear function of other variables:  $X_k = \sum_{j \neq k} c_j X_j$ .
    - dummy variables for all categories of a categorical variable
    - variable multiplied by the constant of another variable

# Which of these would be cases of collinearity and why?

- There is a variable that takes values “white”, “black”, “hispanic”, “asian”, “other”. You include a dummy variable for each category.
- GDP, GDP per capita, and population
- Log GDP, log GDP per capita, and log population
- GDP in millions of dollars; GDP in trillions of dollars
- GDP measured in nominal value; GDP measured in real terms
- Regression with 3 variables and 4 observations

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# Population model in a simple regression

$$Y_i = \alpha + \beta X_i + \epsilon_i$$

Assumptions for statistical inference

1. *X is not invariant:*  $V(X) > 0$
2. *Linearity.* Average value of error given  $x$  is 0.  $E(\epsilon_i) = E(\epsilon_i|x_i) = 0$

$$\mu_i = E(Y_i) = E(Y|X_i) = E(\alpha + \beta X_i + \epsilon_i) = \alpha + \beta x_i$$

3. *Constant variance* Variance of the errors is the same regardless of the value of  $X$

$$V(Y|x_i) = E(\epsilon_i^2) = \sigma_\epsilon^2$$

4. *Independence:* Observations are sampled independently.  $\text{Cor}(\epsilon_i, \epsilon_j) = 0$  for all  $i \neq j$ .
5. Fixed  $X$  or  $X$  measured without error and independent of the error.
6. Errors are normally distributed  $\epsilon_i \sim N(0, \sigma_\epsilon^2)$

# Population model in a multiple regression

$$Y_i = \alpha + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \dots + \beta_k x_{i,k} + \epsilon_i$$

Assumptions for statistical inference

1. *X is not invariant* and no *X* is a perfect linear function of the others.
2. *Linearity*.  $E(\epsilon_i) = 0$
3. *Constant variance*  $V(\epsilon_i) = \sigma_\epsilon^2$
4. *Independence Observations are sampled independently*.  $\text{Cor}(\epsilon_i, \epsilon_j) = 0$  for all  $i \neq j$ .
5. *Fixed X or X measured without error and independent of the error*
6. *Normality* Errors are normally distributed  $\epsilon_i \sim N(0, \sigma_\epsilon^2)$

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# Definitions

**population** The observations of interest. May be theoretical

**sample** The data you have.

**parameter** A function of the population distribution

**statistic** A function of the sample

**sampling distribution** The distribution of a statistic calculated from the distribution of samples of a given size drawn from a population.

See `Sampling_Distributions.Rmd`



# Sampling Distribution of Simple Regression Coefficients

The sampling distributions of  $A$ ,  $B$  given  $Y_i = \alpha + \beta X_i + \epsilon_i$

- expected values (linearity)

$$E(A) = \alpha$$

$$E(B) = \beta$$

- variances (linearity, constant variance, independence)

$$V(A) = \frac{\sigma_{\epsilon}^2}{n} \cdot \frac{\sum x_i^2}{\sum (x_i - \bar{x})^2}$$

$$V(B) = \frac{\sigma_{\epsilon}^2}{\sum (x_i - \bar{x})^2} = \frac{\sigma_{\epsilon}^2}{n V(x)}$$

- normal distribution (normal errors)

$$A \sim N(E(A), V(A))$$

$$B \sim N(E(B), V(B))$$

# Coefficient sampling distributions in multiple regression

The sampling distributions of  $B_k$  given  $Y_i = \alpha + \sum \beta_j X_{j,i} + \epsilon_i$

- Expected value:  $E(B_K) = \beta_k$
- Variance:

$$\begin{aligned} V(B_j) &= \frac{1}{(1 - R_j^2)} \frac{\sigma_\epsilon^2}{\sum (x_{i,j} - \bar{x}_j)^2} \\ &= \frac{\sigma_\epsilon^2}{\sum_i (x_{i,j} - \hat{x}_{i,j})^2} \end{aligned}$$

Where  $R_j^2$  is  $R^2$  from regression of  $X_j$  on other  $X$ , and  $\hat{x}_{ij}$  are fitted values from that regression.

- Normally distributed if errors are normally distributed or as  $n \rightarrow \infty$ .
- $b$  is multivariate normally distributed

$$b \sim N(\beta, \sigma_\epsilon^2 (X'X)^{-1})$$

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# Let's define some things

- statistic** Function of a sample, e.g. Sample mean  $\bar{x} = \frac{1}{n} \sum x_i$
- parameter** Function of the population distribution, e.g. Expected value  $\mu$  of the normal distribution.
- estimator** Method to use a sample statistic (estimate) to infer a population parameter (estimand)

# How to determine if an estimator is good?

- Is  $\hat{\beta} = (X'X)^{-1}X'y$  a good estimator for  $\beta$ ?
- Would another estimator be better?
- First, need criteria to by which to judge estimators

# What makes an estimator good?

- Bias
- Variance
- Efficiency (mean squared error)
- Consistency

# Bias and Variance

## Bias

On average how far off is the estimator?

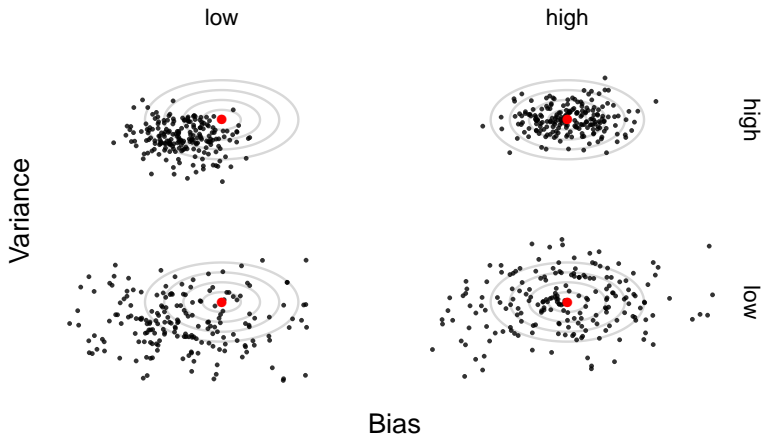
$$\text{bias}(\hat{\beta}) = E(\hat{\beta}) - \beta$$

## Variance

Does the estimator give similar results in different samples?

$$V(\hat{\beta}) = E\left((\beta - E(\hat{\beta}))^2\right)$$

# Bias and Variance Visualized

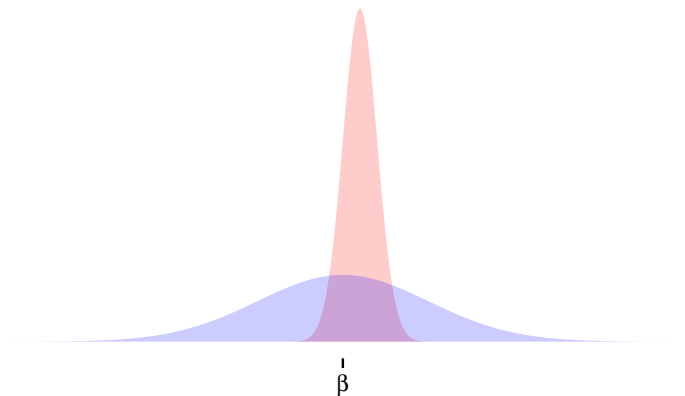




# What makes an estimator good?

- Unbiased methods may still miss the truth by a large amount, just direction not systematic
- Unbiased estimates can be horrible: random draw from numbers 0-24 for time of day
- Biased estimates are not necessarily terrible: a clock that's 2 minutes fast

You may prefer a biased, low variance estimator to an unbiased, high variance estimator



# Mean Squared Error (MSE)

- MSE is

$$MSE(\hat{\beta}) = E((\hat{\beta} - \beta)^2)$$

- MSE trades off bias and variance

$$\begin{aligned} MSE(\hat{\beta}) &= E((\hat{\beta} - E(\hat{\beta}))^2) + E(E(\hat{\beta}) - \beta)^2 \\ &= V(\hat{\beta}) + (\text{bias}(\hat{\beta}, \beta))^2 \end{aligned}$$

- root mean squared error (RMSE)  $\sqrt{MSE}$ : on average how far is an estimate from the truth
- An **efficient** estimator has the smallest MSE
- What is the MSE of an unbiased estimator?

$$MSE(\hat{\beta}) = V(\hat{\beta}) + (\text{bias}(\hat{\beta}, \beta))^2 = V(\hat{\beta}) + 0 = V(\hat{\beta})$$

# MSE Example

- Suppose population parameter  $\beta = 1$
- Consider two estimators  $\hat{\beta}_1$  and  $\hat{\beta}_2$ .
  - $\hat{\beta}_1 \sim N(1, 1^2)$
  - $\hat{\beta}_2 \sim N(0.5, 0.5^2)$
- What are the bias, variance, and MSE of each estimator?

# Consistency

- A consistent estimator converges to the parameter value as the number of observations grows

$$E(\hat{\beta} - \beta) \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

- A concern of econometricians
- May not be as much a concern in finite, small sample sizes
- We will mainly be concerned with efficiency, secondarily with bias, rarely with consistency

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# LS assumptions and consequences of violations

	Assumption		Consequence of violation
1	No perfect collinearity	$\text{rank}(X) = k, k < n$	Coefficients unidentified
2	$X$ is exogenous	$E(X\epsilon) = 0$	Biased, even as $n \rightarrow \infty$
3	Disturbances have mean 0	$E(\epsilon) = 0$	Biased, even as $n \rightarrow \infty$
4	No serial correlation	$E(\epsilon_i \epsilon_j) = 0, i \neq j$	Unbiased but ineff. Wrong se.
5	Homoskedastic errors	$E(\epsilon' \epsilon') = \sigma^2 I$	Unbiased but ineff. Wrong se.
6	Normal errors	$\epsilon \sim N(0, \sigma^2)$	se wrong unless $n \rightarrow \infty$

Assumptions stronger from top to bottom, 4 and 5 could be combined

# Unbiasedness of LS

- Only need assumptions 1-3 (no collinearity,  $X$  exogenous,  $E(\epsilon) = 0$ )
- Start with

$$\begin{aligned}\hat{\beta} &= (X'X)^{-1}X'(X\beta + \epsilon) \\ &= \beta + (X'X)^{-1}X'\epsilon\end{aligned}$$

- Take the expectation

$$\begin{aligned}E(\hat{\beta}) &= E(\beta) + E(X'X)^{-1}X'E(\epsilon) \\ &= E(\beta) + X'X)^{-1}X'E(\epsilon) \\ &= E(\beta)\end{aligned}$$

- Since  $E(\hat{\beta}) = E(\beta)$ , LS is unbiased.



# Gauss-Markov

- If make assumptions 1–5: LS is the best linear unbiased estimator (BLUE)
- LS estimator is **linear** because  $\hat{\beta} = My$ , where  $M = (X'X)^{-1}X'$
- **best** is best mean squared error (MSE).
- If LS is unbiased, then its mean squared error is the same as its ...?
- Could exist other non-linear unbiased estimators with smaller MSE, e.g. Robust regression when population has fat tailed errors
- If errors are Gaussian, LS is Minimum Variance Unbiased (MVU).
- MVU = for *all* estimators that are unbiased.  $\hat{\beta}$  has smallest variance (and MSE).

# References

- Some slides derived from Christopher Adolph *Linear Regression in Matrix Form / Properties & Assumptions of Linear Regression*. Used with permission.  
<<http://faculty.washington.edu/cadolph/503/topic3.pw.pdf>>
- Material included from
  - Fox Ch 6, 9.3
  - Angrist and Pischke, Chapter 3

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