

# TWO-VARIABLE REGRESSION MODEL: THE PROBLEM OF ESTIMATION

The Two-Variable PRF:

$$Y_i = \beta_1 + \beta_2 X_i + u_i$$

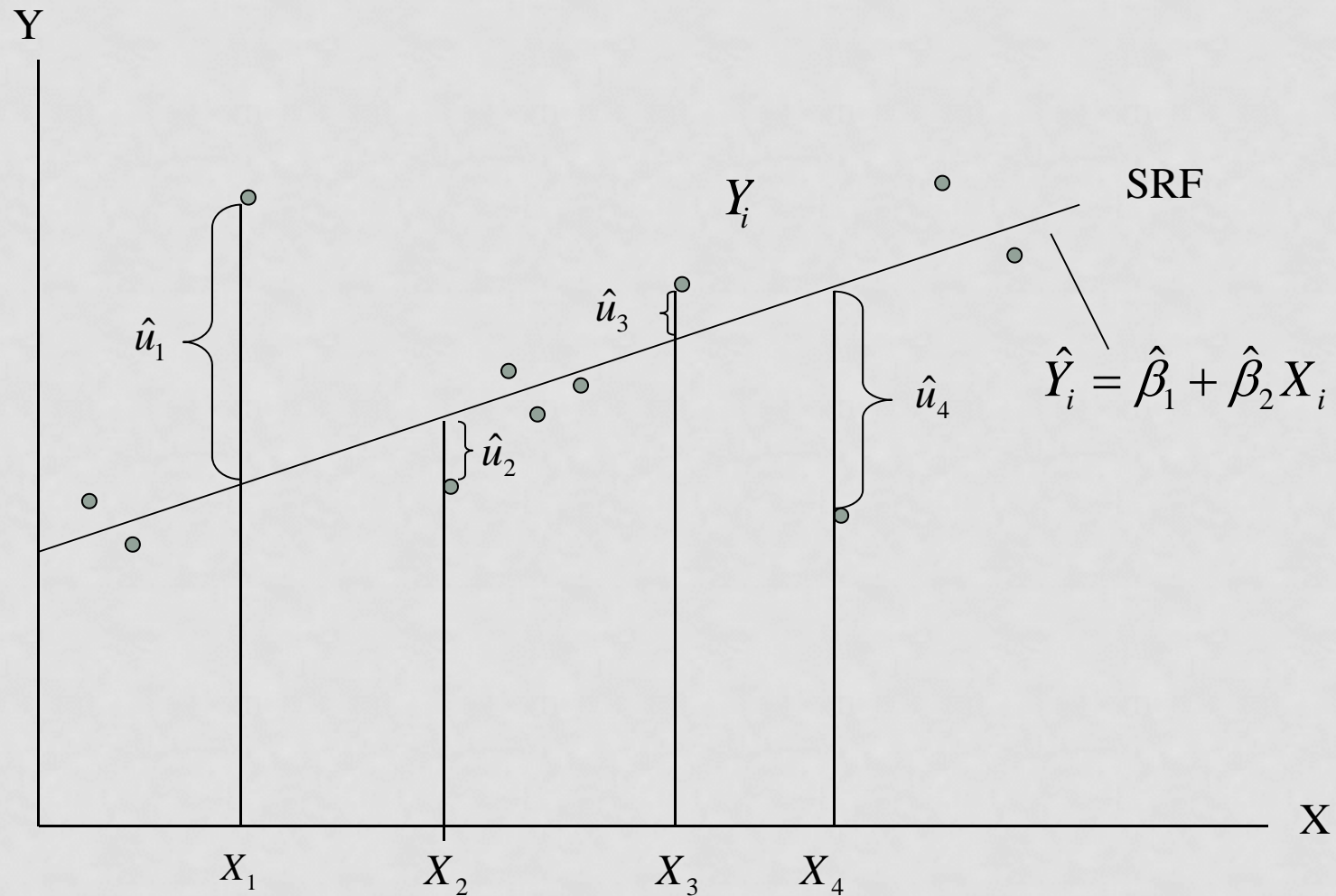
The Two-Variable SRF:

$$\begin{aligned} Y_i &= \hat{\beta}_1 + \hat{\beta}_2 X_i + \hat{u}_i \\ &= \hat{Y}_i + \hat{u}_i \end{aligned}$$

$\hat{Y}_i$  is the estimated (conditional mean) value of  $Y_i$

$$\begin{aligned}\hat{u}_i &= Y_i - \hat{Y}_i \\ &= Y_i - \hat{\beta}_1 - \hat{\beta}_2 X_i\end{aligned}$$

# ORDINARY LEAST SQUARES (OLS)



# ORDINARY LEAST SQUARES (OLS)

$$\begin{aligned}\sum \hat{u}_i^2 &= \sum (Y_i - \hat{Y}_i)^2 \\ &= \sum (Y_i - \hat{\beta}_1 - \hat{\beta}_2 X_i)^2\end{aligned}$$

The principle or the method of least squares chooses  $\hat{\beta}_1$  and  $\hat{\beta}_2$  in such a manner that, for a given sample or set of data,  $\sum \hat{u}_i^2$  is as small as possible

$$\sum \hat{u}_i^2 = f(\hat{\beta}_1, \hat{\beta}_2)$$

$$\frac{\partial \left( \sum \hat{u}_i^2 \right)}{\partial \hat{\beta}_1} = -2 \sum \left( Y_i - \hat{\beta}_1 - \hat{\beta}_2 X_i \right) = -2 \sum \hat{u}_i$$

$$\frac{\partial \left( \sum \hat{u}_i^2 \right)}{\partial \hat{\beta}_2} = -2 \sum \left( Y_i - \hat{\beta}_1 - \hat{\beta}_2 X_i \right) X_i = -2 \sum \hat{u}_i X_i$$

Setting these equation to zero

$$\sum Y_i = n\hat{\beta}_1 + \hat{\beta}_2 \sum X_i$$

$$\sum Y_i X_i = \hat{\beta}_1 \sum X_i + \hat{\beta}_2 \sum X_i^2$$

Where  $n$  is the sample size. These simultaneous equations are known as the **Normal Equation**

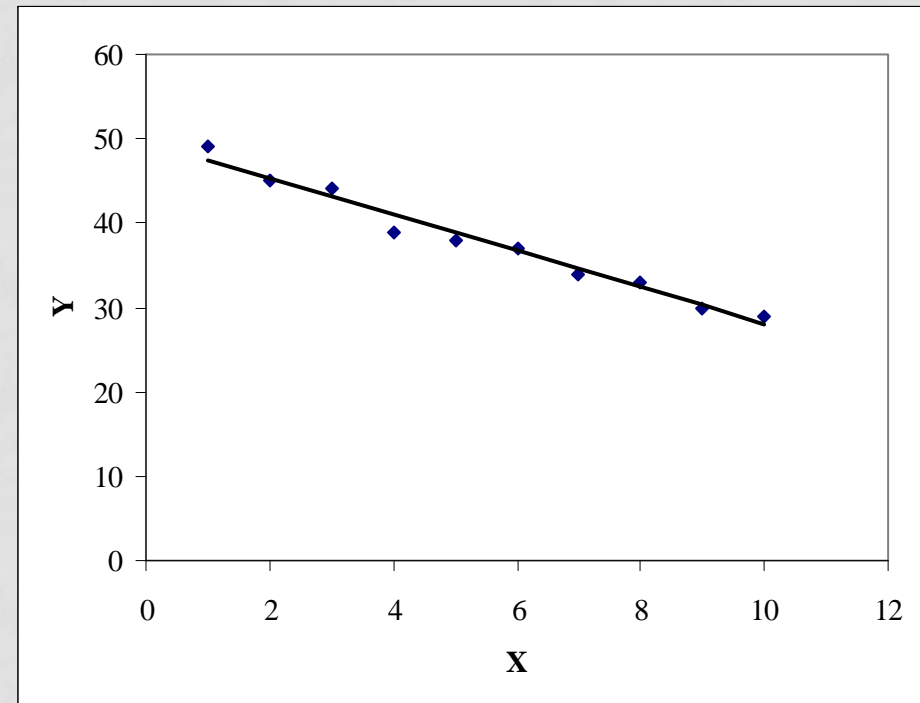
$$\begin{aligned}\hat{\beta}_2 &= \frac{n \sum X_i Y_i - \sum X_i \sum Y_i}{n \sum X_i^2 - (\sum X_i)^2} \\ &= \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2} \\ &= \frac{\sum x_i y_i}{\sum x_i^2}\end{aligned}$$

$$\begin{aligned}\hat{\beta}_2 &= \frac{\sum x_i y_i}{\sum x_i^2} \\ &= \frac{\sum x_i Y_i}{\sum X_i^2 - n\bar{X}^2} \\ &= \frac{\sum X_i y_i}{\sum X_i^2 - n\bar{X}^2}\end{aligned}$$

$$\hat{\beta}_1 = \frac{\sum X_i^2 \sum Y_i - \sum X_i \sum X_i Y_i}{n \sum X_i^2 - (\sum X_i)^2}$$
$$= \bar{Y} - \hat{\beta}_2 \bar{X}$$

# EXAMPLE 😊

Y	X
49	1
45	2
44	3
39	4
38	5
37	6
34	7
33	8
30	9
29	10



$$\hat{\beta}_2 = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2} = \frac{-178}{82.5} \approx -2.1576$$

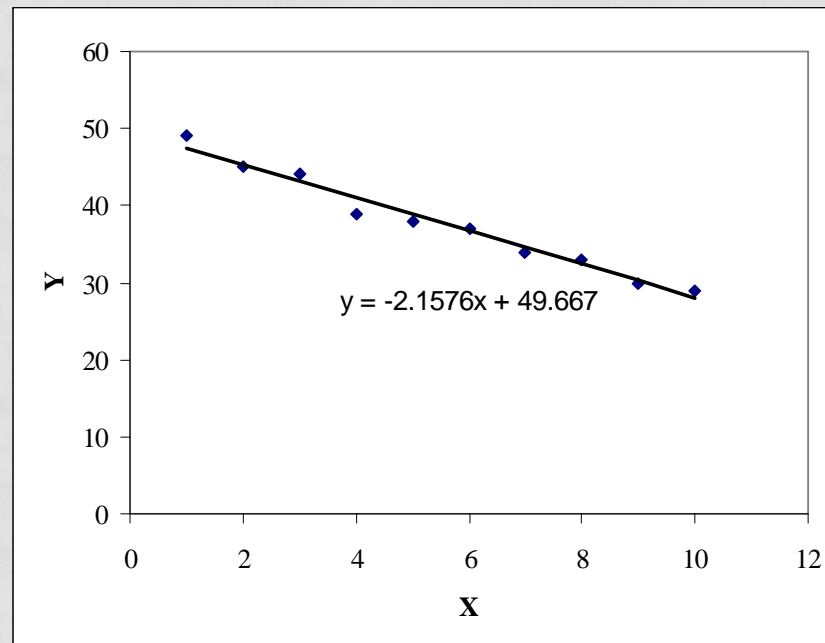
$$\hat{\beta}_1 = \bar{Y} - \hat{\beta}_2 \bar{X} = 37.8 - (-2.1576)(5.5) = 49.667$$

$$\bar{X} = 5.5$$

$$\bar{Y} = 37.8$$

Y	X	$(X_i - \bar{X})$	$(X_i - \bar{X})^2$	$Y_i - \bar{Y}$	$(X_i - \bar{X})(Y_i - \bar{Y})$
49	1	-4.5	20.25	11.2	-50.4
45	2	-3.5	12.25	7.2	-25.2
44	3	-2.5	6.25	6.2	-15.5
39	4	-1.5	2.25	1.2	-1.8
38	5	-0.5	0.25	0.2	-0.1
37	6	0.5	0.25	-0.8	-0.4
34	7	1.5	2.25	-3.8	-5.7
33	8	2.5	6.25	-4.8	-12
30	9	3.5	12.25	-7.8	-27.3
29	10	4.5	20.25	-8.8	-39.6
			82.5		-178

$$\hat{Y}_i = 49.667 - 2.1576X_i$$



# PRACTICE I

A Random Sample from the Population  
of Table 2.1

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Weekly consumption expenditure \$ (Y)	Weekly income \$(X)
70	80
65	100
90	120
95	140
110	160
115	180
120	200
140	220
155	240
150	260

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$$\hat{Y} = 0.5091X_i + 24.455$$

# PRACTICE II

Another Random Sample from the  
Population of Table 2.1

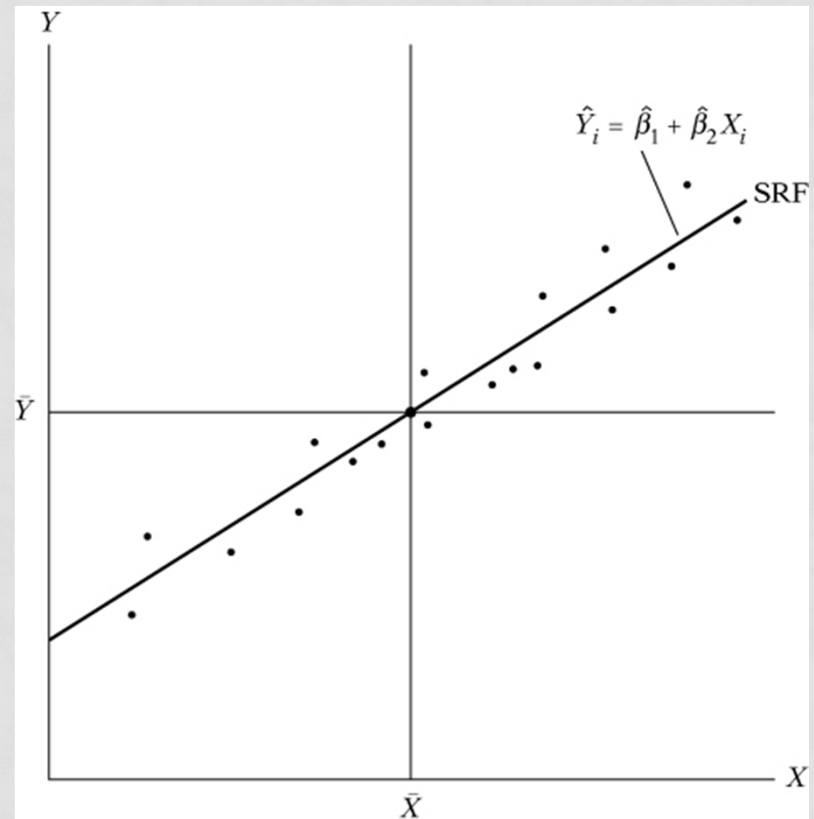
Weekly consumption expenditure \$ (Y)	Weekly income \$(X)
Y	X
55	80
88	100
90	120
80	140
118	160
120	180
145	200
135	220
145	240
175	260

$$\hat{Y} = 0.5761X_i + 17.17$$

- The estimators obtained are known as the least-squares estimators
- The statistical properties of OLS estimators – properties that hold only under certain assumptions about the way the data were generated
  - The OLS estimators are expressed solely in terms of the observable (i.e. sample) quantities (i.e.,  $X$  and  $Y$ )
  - They are point estimators
  - Once the OLS estimates are obtained from the sample data, the sample regression line can be easily obtained.

# THE REGRESSION LINE HAS THE FOLLOWING PROPERTIES:

- Passes through the sample means of Y and X



- The mean value of the estimated  $Y = \hat{Y}_i$  is equal to the mean value of the actual Y for

$$\hat{Y}_i = \hat{\beta}_1 + \hat{\beta}_2 X_i$$

- The mean value of the residuals  $\hat{u}_i$  is zero
- The residuals  $\hat{u}_i$  are uncorrelated with the predicted  $Y_i$
- The residuals  $\hat{u}_i$  are uncorrelated with  $X_i$

# CLASSICAL LINEAR REGRESSION MODEL (CLRM)

The assumptions underlying the method of least squares:

1. Linear regression model
2. Fixed  $X$  values or  $X$  values independent of the error  $u_i$  term
3. Zero mean value of disturbance  $u_i$
4. Homoscedasticity or Constant Variance of
5. No autocorrelation between the disturbances
6. The number of observations  $n$  must be greater than the number of parameters to be estimated
7. The nature of  $X$  variables

# LINEAR REGRESSION MODEL

$$Y_i = \beta_1 + \beta_2 X_i + u_i$$

- Linear in the parameters
- May or may not be linear in the variables

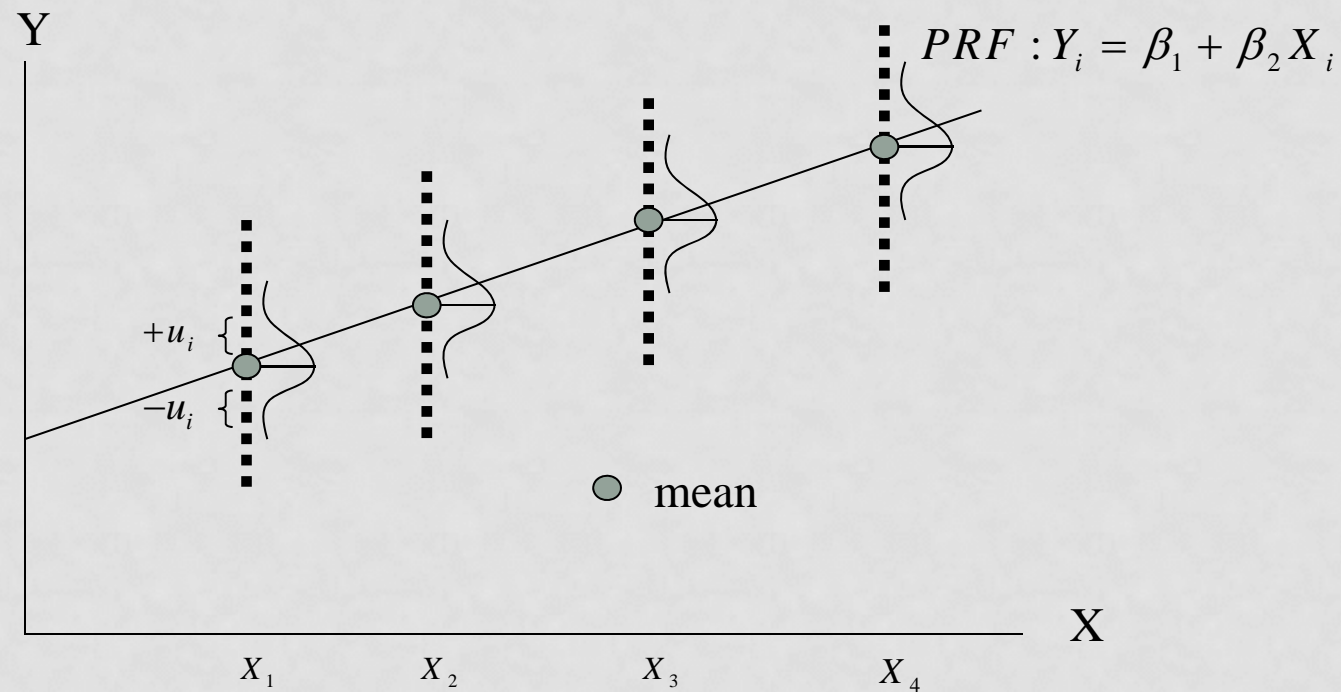
# X VALUES INDEPENDENT OF THE ERROR TERM

$$\text{Cov}(X_i, u_i) = 0$$

# ZERO MEAN VALUE OF DISTURBANCE TERM

$$E(u_i | X_i) = 0$$

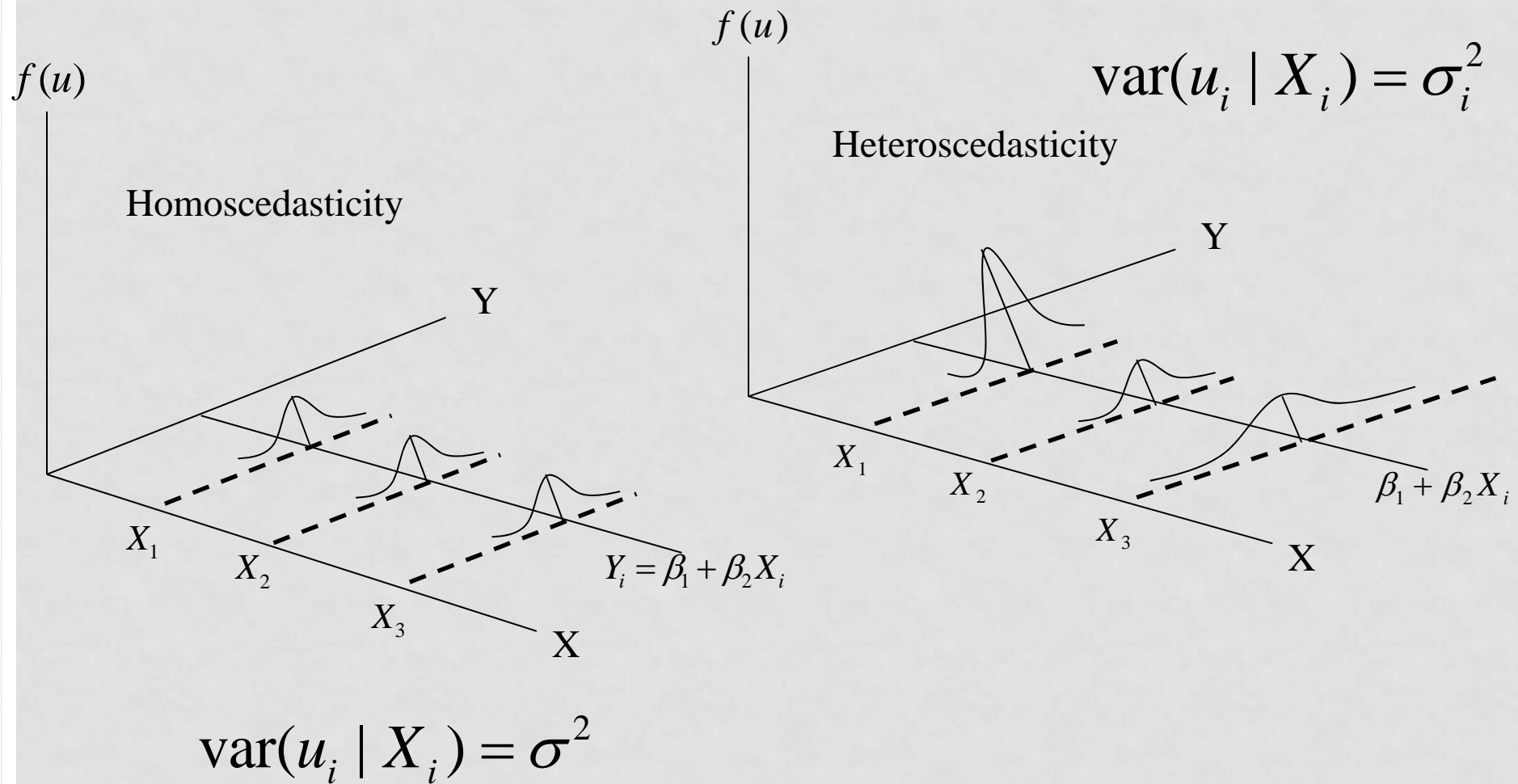
$$E(u_i) = 0$$



# HOMOSCEDASTICITY

$$\begin{aligned}\text{var}(u_i) &= E[u_i - E(u_i | X_i)]^2 \\ &= E(u_i^2 | X_i), \text{ because of assumption 3} \\ &= E(u_i^2), \text{ if } X_i \text{ are nonstochastic} \\ &= \sigma^2\end{aligned}$$

# HOMOSCEDASTICITY VS. HETEROSCEDASTICITY



# HOMOSCEDASTICITY V.S. HETEROSCEDASTICITY

## **Homoscedasticity**

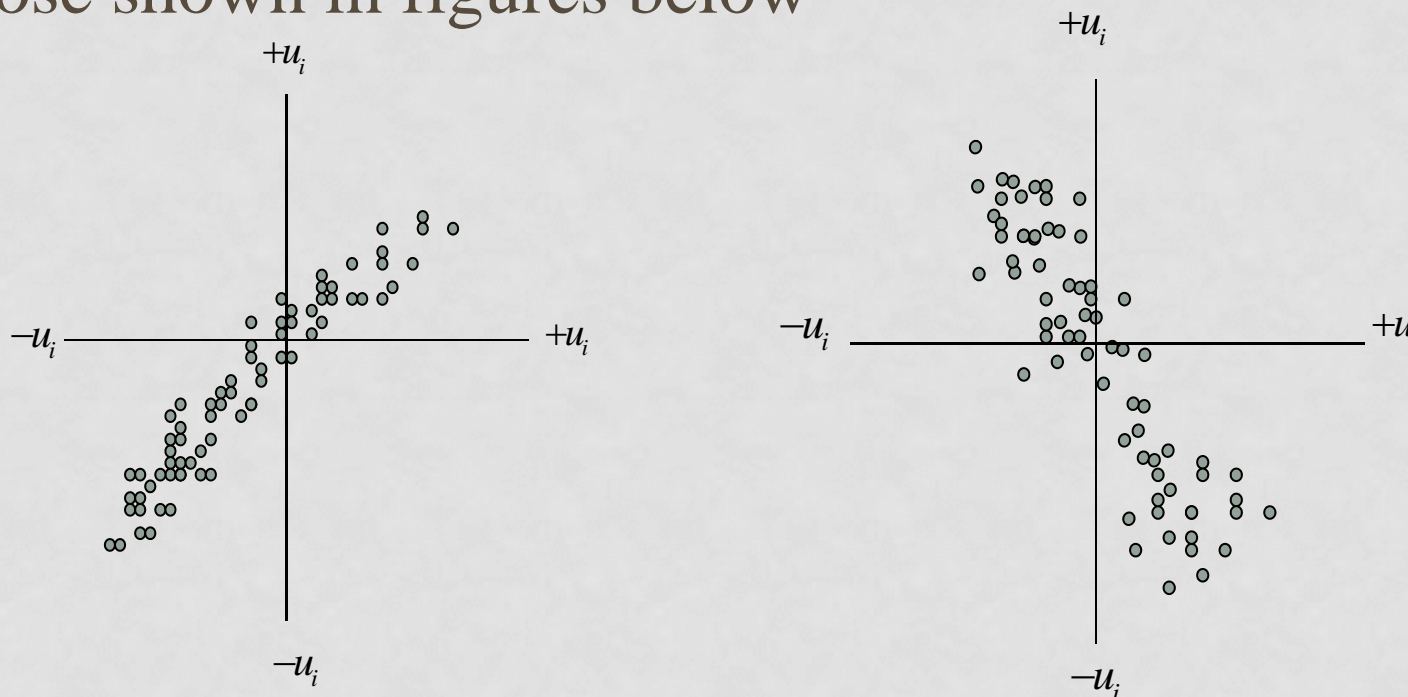
- Equal variance
- The variation around the regression line is the same across the  $X$  values

## **Heteroscedasticity**

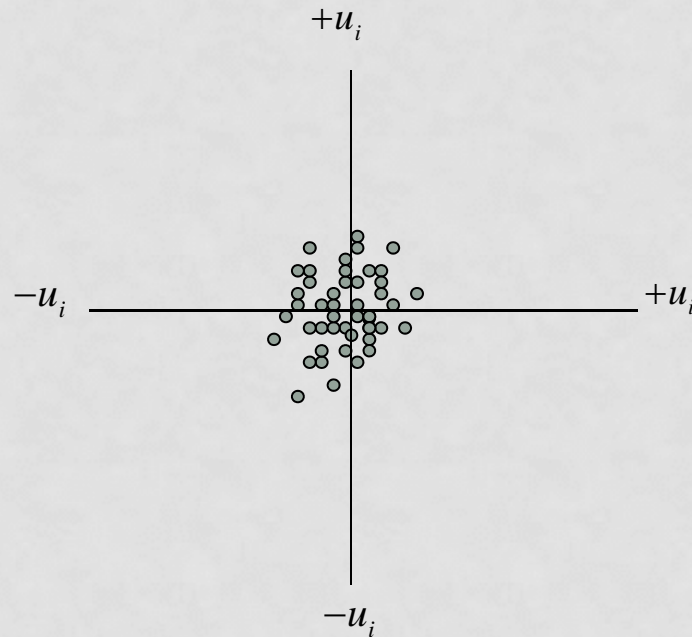
- Unequal variance

# NO AUTOCORRELATION BETWEEN THE DISTURBANCES

Given  $X_i$ , the deviations of any two Y values from their mean value do not exhibit patterns such as those shown in figures below



# NO AUTOCORRELATION BETWEEN THE DISTURBANCES



## NO AUTOCORRELATION BETWEEN THE DISTURBANCES

Given any two  $X$  values,  $X_i$  and  $X_j (i \neq j)$ , the correlation between any two  $u_i$  and  $u_j (i \neq j)$  is zero.

$$\text{cov}(u_i, u_j | X_i, X_j) = 0$$

$$\text{cov}(u_i, u_j) = 0, \text{ if } X \text{ is nonstochastic}$$

Where  $i$  and  $j$  are two different observation and where cov means covariance

THE NUMBER OF OBSERVATIONS  $N$  MUST BE GREATER  
THAN THE NUMBER OF PARAMETERS TO BE  
ESTIMATED

The number of observations must be greater than the number of explanatory variables

# THE NATURE OF $X$ VARIABLES

- The  $X$  values in a given sample must not all be the same
- No outliers in the  $X$  values

# STANDARD ERRORS OF LEAST-SQUARES ESTIMATES

$$\text{var}(\hat{\beta}_2) = \frac{\sigma^2}{\sum x_i^2}$$

$$se(\hat{\beta}_2) = \frac{\sigma}{\sqrt{\sum x_i^2}}$$

$$\text{var}(\hat{\beta}_1) = \frac{\sum X_i^2}{n \sum x_i^2} \sigma^2$$

$$se(\hat{\beta}_1) = \sqrt{\frac{\sum X_i^2}{n \sum x_i^2}} \sigma$$

$$\hat{\sigma}^2 = \frac{\sum \hat{u}_i^2}{n - 2}$$

$\hat{\sigma}^2$  is the OLS estimator of the true but unknown  $\sigma^2$

The expression  $n-2$  is known as the number of degrees of freedom

$\sum \hat{u}_i^2$  is the sum of the residuals squared or residual sum of squares (RSS)

$$\begin{aligned} \text{COV}(\hat{\beta}_1, \hat{\beta}_2) &= -\bar{X} \text{var}(\hat{\beta}_2) \\ &= -\bar{X} \left( \frac{\sigma^2}{\sum x_i^2} \right) \\ &= \frac{-\bar{X} \sigma^2}{\sum (X_i - \bar{X})^2} \end{aligned}$$

Y	X
49	1
45	2
44	3
39	4
38	5
37	6
34	7
33	8
30	9
29	10

## EXAMPLE 😊

$$\hat{\beta}_1 = 49.667$$

$$\hat{\beta}_2 = -2.1576$$

$$\bar{X} = 5.5$$

Y	X	$\hat{Y}_i = \hat{\beta}_1 + \hat{\beta}_2 X_i$	$\hat{u}_i$	$\hat{u}_i^2$	$(X_i - \bar{X})^2$	$X_i^2$
49	1	47.5094	1.4906	2.2219	20.25	1
45	2	45.3518	-0.352	0.1238	12.25	4
44	3	43.1942	0.8058	0.6493	6.25	9
39	4	41.0366	-2.037	4.1477	2.25	16
38	5	38.879	-0.879	0.7726	0.25	25
37	6	36.7214	0.2786	0.0776	0.25	36
34	7	34.5638	-0.564	0.3179	2.25	49
33	8	32.4062	0.5938	0.3526	6.25	64
30	9	30.2486	-0.249	0.0618	12.25	81
29	10	28.091	0.909	0.8263	20.25	100
			Total	9.5515	82.5	385

$$\hat{\sigma}^2 = \frac{\sum \hat{u}_i^2}{n-2} = \frac{9.5515}{10-2} = 1.1939$$

$$\text{var}(\hat{\beta}_2) = \frac{\hat{\sigma}^2}{\sum x_i^2} = \frac{\hat{\sigma}^2}{\sum (X_i - \bar{X})^2} = \frac{1.1939}{82.5} = 0.0145$$

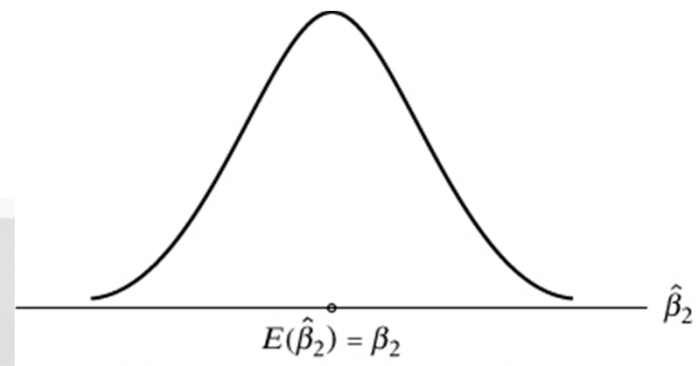
$$\text{var}(\hat{\beta}_1) = \frac{\sum X_i^2}{n \sum x_i^2} \hat{\sigma}^2 = \frac{\sum X_i^2}{n \sum (X_i - \bar{X})^2} \hat{\sigma}^2 = \frac{(1.1939)(385)}{(10)(82.5)} = 0.5572$$

$$\text{COV}(\hat{\beta}_1, \hat{\beta}_2) = -\bar{X} \text{var}(\hat{\beta}_2) = -(5.5)(0.0145) = -0.07975$$

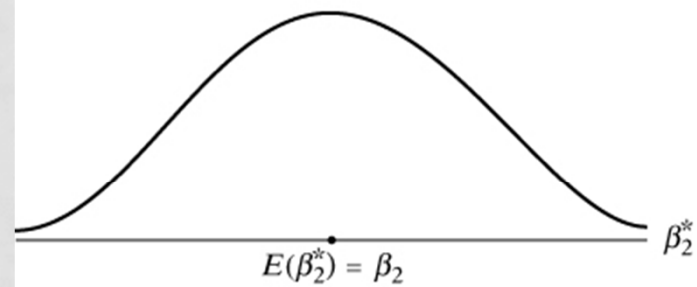
# PROPERTIES OF LEAST-SQUARES ESTIMATORS: THE GAUSS-MARKOV THEOREM

Best Linear Unbiased Estimator (BLUE) of  $\beta_2$  :

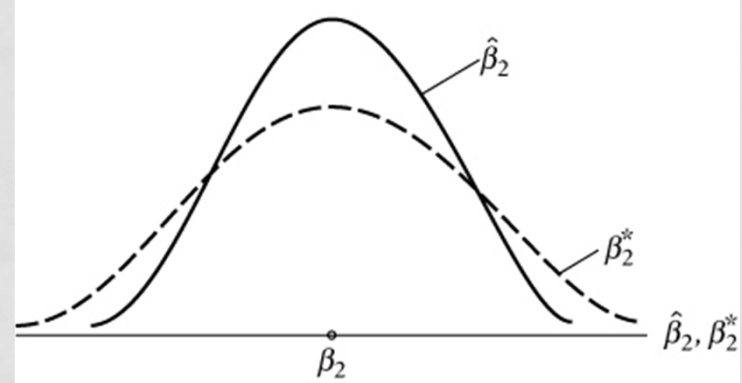
- It is linear, that is, a linear function of a random variable, such as the dependent variable  $Y$  in the regression model
- It is unbiased  $E(\hat{\beta}_2) = \beta_2$
- Efficient estimator – an unbiased estimator with the least variance



(a) Sampling distribution of  $\beta_2$



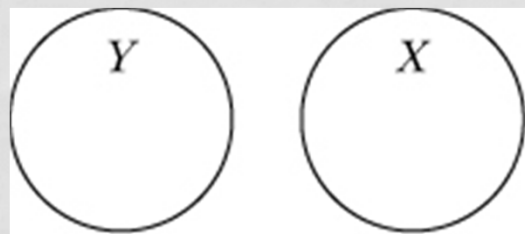
(b) Sampling distribution of  $\beta_2^*$



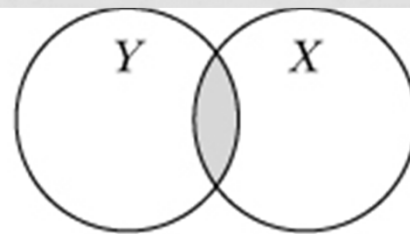
(c) Sampling distributions of  $\beta_2$  and  $\beta_2^*$

# THE COEFFICIENT OF DETERMINATION $r^2$

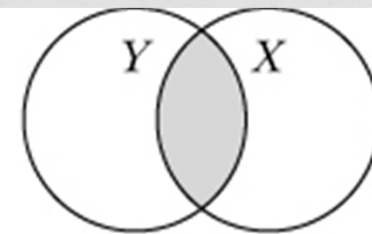
- A measure of goodness of fit
- A summary measure that tells how well the sample regression line fits the data
- Measures the proportion or percentage of the total variation in  $Y$  explained by the regression model



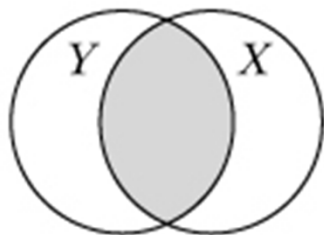
(a)



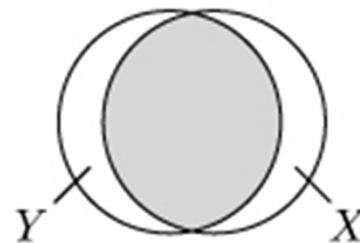
(b)



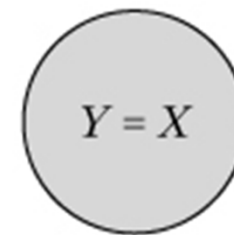
(c)



(d)



(e)



(f)

TO COMPUTE THIS  $r^2$

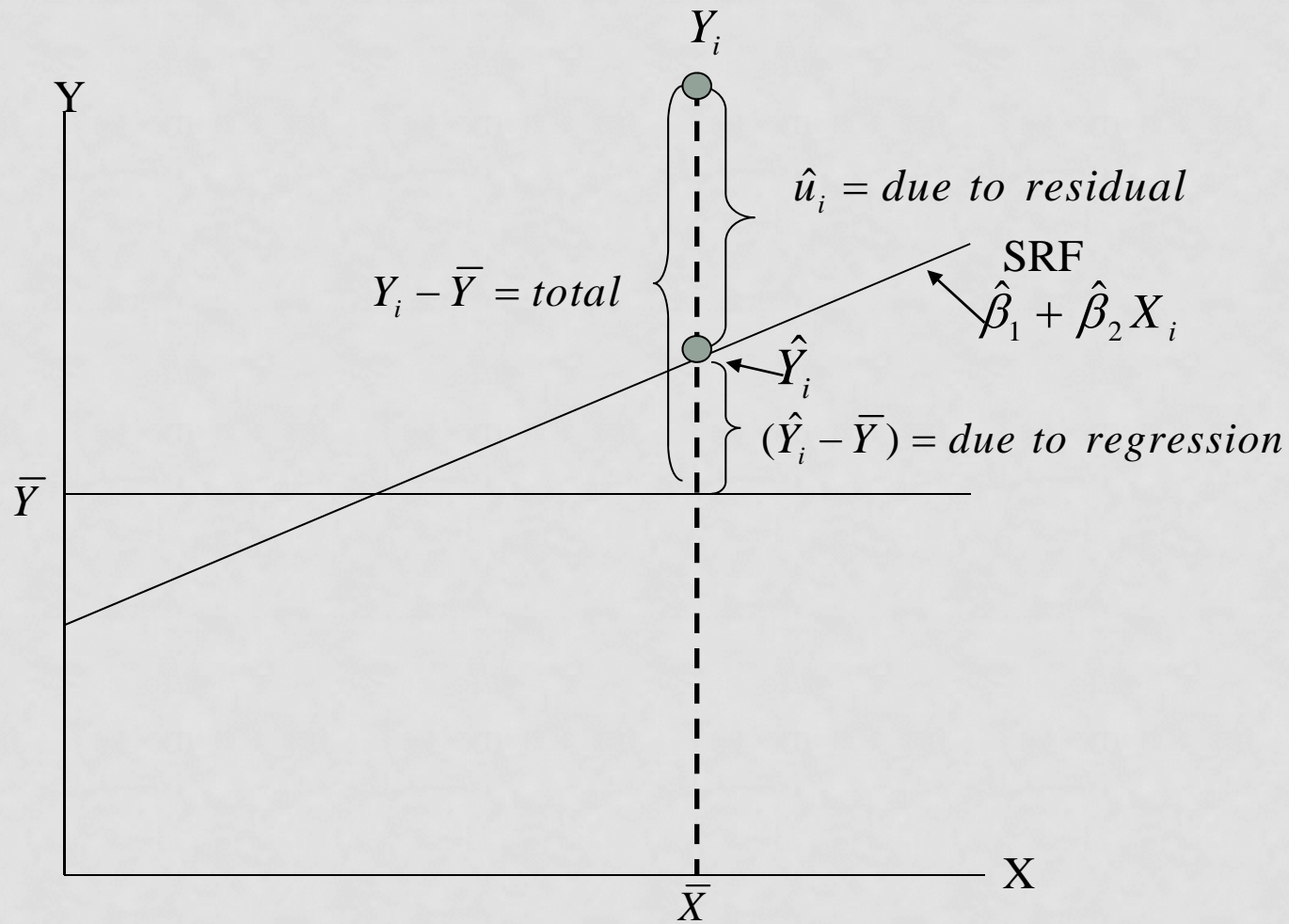
$$Y_i = \hat{Y}_i + \hat{u}_i$$

$$y_i = \hat{y}_i + \hat{u}_i$$

$$\sum y_i^2 = \sum \hat{y}_i^2 + \sum \hat{u}_i^2 + 2 \sum \hat{y}_i \hat{u}_i$$

$$= \sum \hat{y}_i^2 + \sum \hat{u}_i^2$$

$$= \hat{\beta}_2^2 \sum x_i^2 + \sum \hat{u}_i^2$$



$$\sum y_i^2 = \sum (Y_i - \bar{Y})^2$$

**Total variation of the actual Y values about their sample mean**  
**(Total Sum of Squares, TSS)**

$$\sum \hat{y}_i^2 = \sum (\hat{Y}_i - \hat{Y})^2 = \hat{\beta}_2^2 \sum x_i^2$$

**Variation of the estimated Y values about their mean**  
**(Explained Sum of Squares, ESS)**

$$\sum \hat{u}_i^2$$

**Residual or unexpected variation of the Y values about the regression line (Residual Sum of Squares, RSS)**

$$TSS = ESS + RSS$$

$$\begin{aligned} 1 &= \frac{ESS}{TSS} + \frac{RSS}{TSS} \\ &= \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} + \frac{\sum \hat{u}_i^2}{\sum (Y_i - \bar{Y})^2} \\ r^2 &= \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} = \frac{ESS}{TSS} \end{aligned}$$

Y	X
49	1
45	2
44	3
39	4
38	5
37	6
34	7
33	8
30	9
29	10

## EXAMPLE ☺

$$\hat{\beta}_1 = 49.667$$

$$\hat{\beta}_2 = -2.1576$$

$$\bar{X} = 5.5$$

$$\bar{Y} = 38$$

Y	X	$\hat{Y}_i = \hat{\beta}_1 + \hat{\beta}_2 X_i$	$\hat{u}_i$	$(Y_i - \bar{Y})^2$	$(\hat{Y}_i - \bar{Y})^2$	$\hat{u}_i^2$
49	1	47.509	1.491	125.44	94.27	2.22
45	2	45.352	-0.352	51.84	57.03	0.12
44	3	43.194	0.806	38.44	29.10	0.65
39	4	41.037	-2.037	1.44	10.48	4.15
38	5	38.879	-0.879	0.04	1.16	0.77
37	6	36.721	0.279	0.64	1.16	0.08
34	7	34.564	-0.564	14.44	10.47	0.32
33	8	32.406	0.594	23.04	29.09	0.35
30	9	30.249	-0.249	60.84	57.02	0.06
29	10	28.091	0.909	77.44	94.26	0.83
				393.6	384.06	9.55

$$r^2 = \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} = \frac{ESS}{TSS}$$

$$r^2 = \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} = \frac{384.06}{393.6} \approx 0.98$$

Approximately 98 percent of the variation in Y is explained by variation in X.

## TWO PROPERTIES OF $r^2$

1. Nonnegative quantity
2. Its limits are  $0 \leq r^2 \leq 1$

# THE COEFFICIENT OF CORRELATION: R

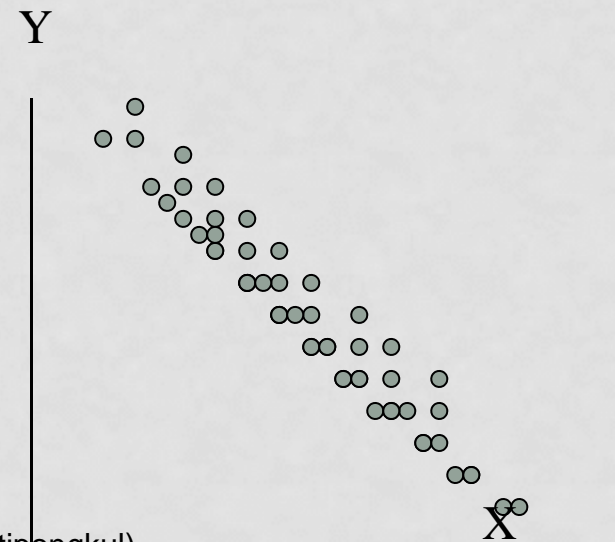
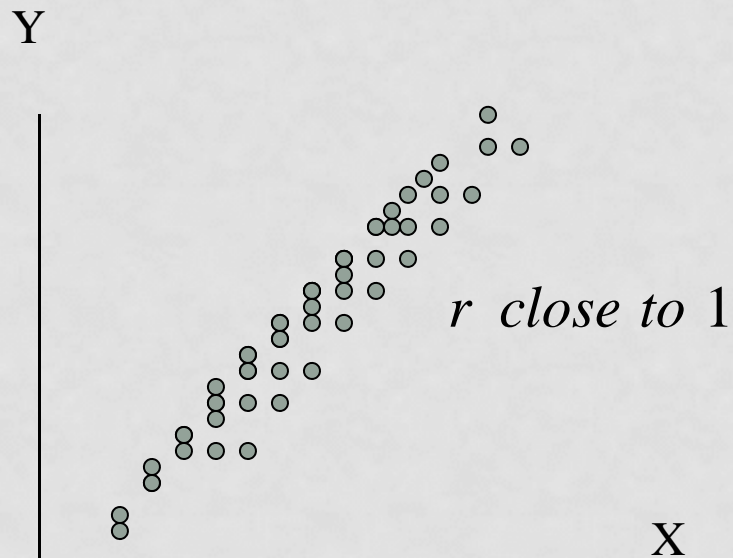
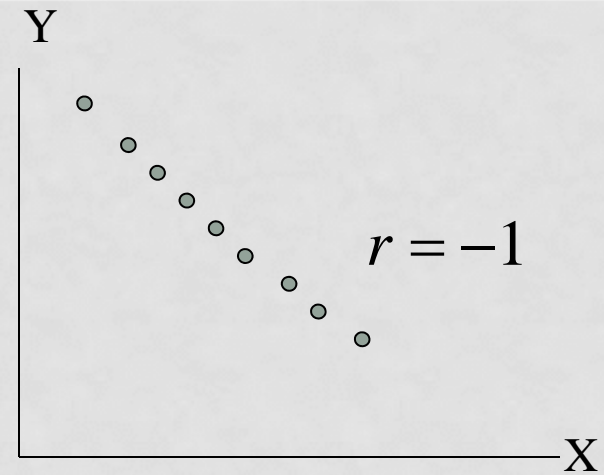
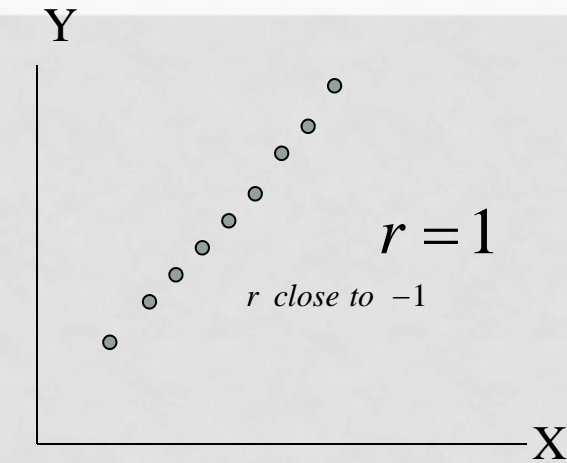
- A measure of the degree of association between two variables

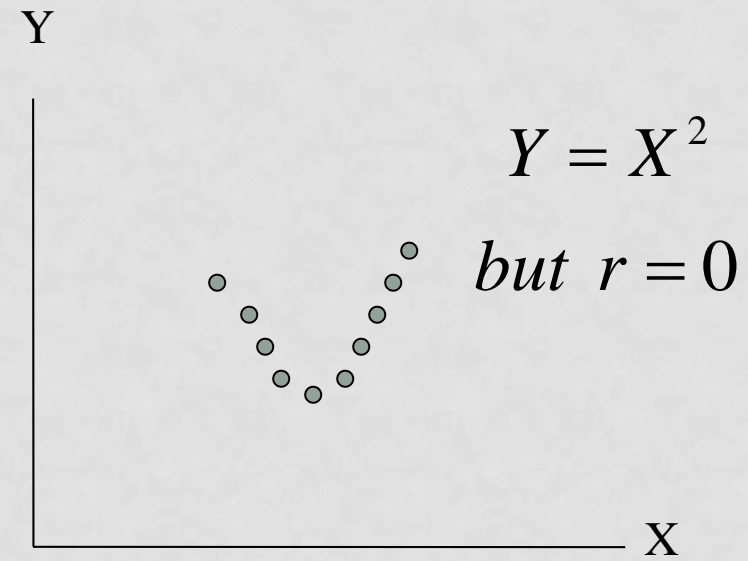
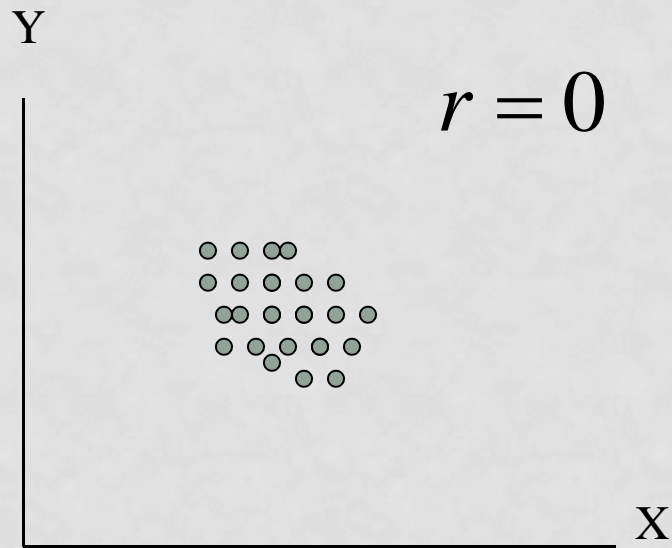
$$r = \pm\sqrt{r^2}$$

# PROPERTIES OF $r$

1. Can be positive or negative
2. Lies between the limits of -1 and 1
3. Symmetric in nature
4. Independent of the origin and scale
5. If X and Y are statistically independent, the correlation coefficient between them is zero **but zero correlation does not necessarily imply independence**
6. No meaning for describing nonlinear relations
7. Does not necessarily imply any cause and effect relationship

# CORRELATION PATTERNS





# SOURCE

Gujarati, D.N. (2009) Basic Econometrics. 5th ed.  
Singapore, McGraw-Hill.