

Topic 3: Simple Linear Regression

Outline

- **Simple linear regression model**
 - **Model parameters**
 - **Distribution of error terms**
- **Estimation of regression parameters**
 - **Method of least squares**
 - **Maximum likelihood**

Data for Simple Linear Regression

- Observe $i=1,2,\dots,n$ pairs of variables
- Each pair often called a case
- $Y_i = i^{\text{th}}$ response variable
- $X_i = i^{\text{th}}$ explanatory variable

Simple Linear Regression Model

- $Y_i = b_0 + b_1 X_i + e_i$
- b_0 is the intercept
- b_1 is the slope
- e_i is a random error term
 - $E(e_i)=0$ and $s^2(e_i)=s^2$
 - e_i and e_j are uncorrelated

Simple Linear Normal Error **Regression Model**

- $Y_i = b_0 + b_1 X_i + e_i$
- b_0 is the intercept
- b_1 is the slope
- e_i is a Normally distributed random error with mean 0 and variance σ^2
- e_i and e_j are uncorrelated \rightarrow indep

Model Parameters

- β_0 : the intercept
- β_1 : the slope
- σ^2 : the variance of the error term

Features of Both Regression Models

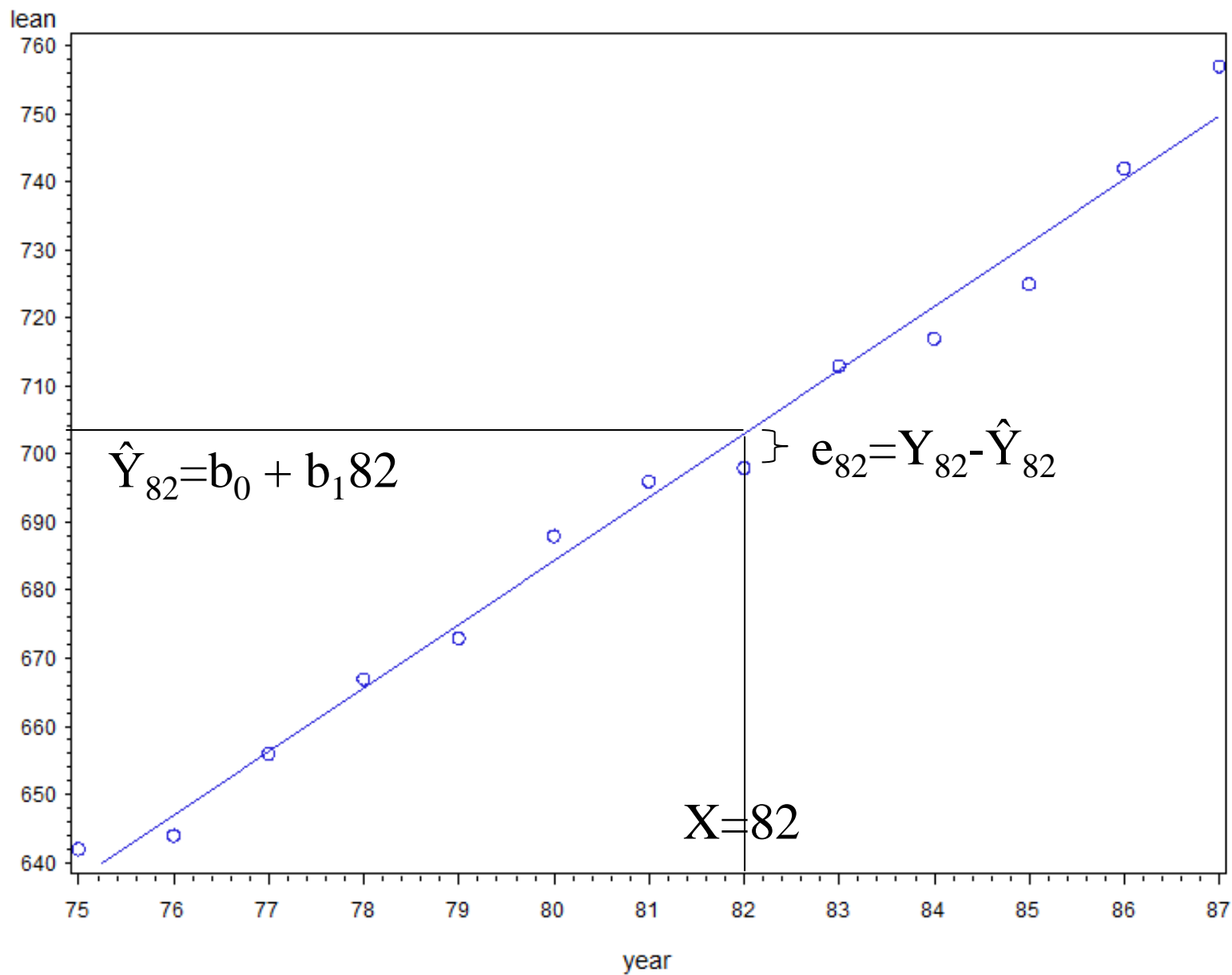
- $Y_i = \beta_0 + \beta_1 X_i + e_i$
- $E(Y_i) = \beta_0 + \beta_1 X_i + E(e_i) = \beta_0 + \beta_1 X_i$
- $\text{Var}(Y_i) = 0 + \text{var}(e_i) = \sigma^2$
 - Mean of Y_i determined by value of X_i
 - All possible means fall on a line
 - The Y_i vary about this line

Features of Normal Error Regression Model

- $Y_i = \beta_0 + \beta_1 X_i + e_i$
- If e_i is Normally distributed then
 Y_i is $N(\beta_0 + \beta_1 X_i, \sigma^2)$ (A.36)
- Does not imply the collection of Y_i are Normally distributed

Fitted Regression Equation **and Residuals**

- $\hat{Y}_i = b_0 + b_1 X_i$
 - b_0 is the estimated intercept
 - b_1 is the estimated slope
- e_i : residual for i^{th} case
- $e_i = Y_i - \hat{Y}_i = Y_i - (b_0 + b_1 X_i)$



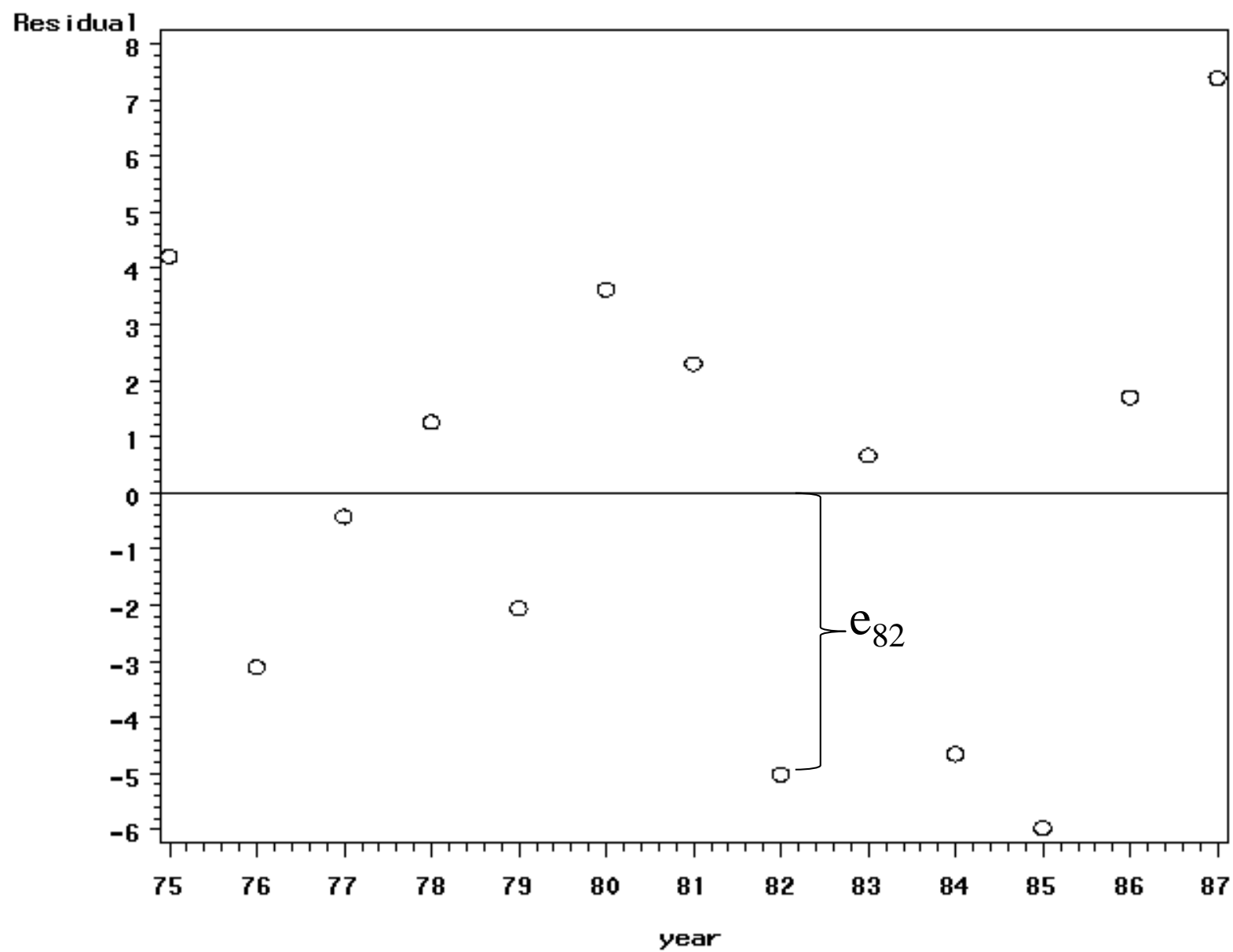
Plot the residuals

Continuation of pisa.sas

Using data set from output statement

```
proc gplot data=a2;  
  plot resid*year vref=0;  
  where lean ne .;  
run;
```

vref=0 adds horizontal line to plot at zero



Least Squares

- Want to find “best” b_0 and b_1
- Will minimize $\Sigma(Y_i - (b_0 + b_1 X_i))^2$
- Use calculus: take derivative with respect to b_0 and with respect to b_1 and set the two resulting equations equal to zero and solve for b_0 and b_1
- See KNNL pgs 16-17

Least Squares Solution

$$b_1 = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2}$$

$$b_0 = \bar{Y} - b_1 \bar{X}$$

- **These are also maximum likelihood estimators for Normal error model, see KNNL pp 30-32**

Maximum Likelihood

$$Y_i \sim N(\beta_0 + \beta_1 X_i, \sigma^2)$$

$$f_i = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{Y_i - \beta_0 - \beta_1 X_i}{\sigma}\right)^2}$$

$$L = f_1 \cdot f_2 \cdot \dots \cdot f_n \text{ (likelihood function)}$$

Find β_0 and β_1 which maximizes L

Estimation of σ^2

$$s^2 = \frac{\sum (Y_i - \hat{Y}_i)^2}{n - 2} = \frac{\sum e_i^2}{n - 2}$$

$$= \frac{SSE}{df_E} = MSE$$

$$s = \sqrt{s^2} = \text{Root } MSE$$

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	15804	15804	904.12	<.0001
Error	11	192.28571	17.48052		
Corrected Total	12	15997			

df_e

Root MSE	4.18097	R-Square	0.9880
Dependent Mean	693.69231	Adj R-Sq	0.9869
Coeff Var	0.60271		

MSE

S

Standard output from Proc REG

Properties of Least Squares

Line

- **The line always goes through (\bar{X}, \bar{Y})**
- $$\begin{aligned}\sum e_i &= \sum (Y_i - (b_0 + b_1 X_i)) \\ &= \sum Y_i - \sum b_0 - \sum b_1 X_i \\ &= n\bar{Y} - nb_0 - nb_1\bar{X} = n((\bar{Y} - b_1\bar{X}) - b_0) \\ &= 0\end{aligned}$$
- **Other properties on pgs 23-24**

Background Reading

- **Chapter 1**
 - 1.6 : Estimation of regression function
 - 1.7 : Estimation of error variance
 - 1.8 : Normal regression model
- **Chapter 2**
 - 2.1 and 2.2 : inference concerning β 's
- **Appendix A**
 - A.4, A.5, A.6, and A.7