

Econometrics. 2022-3-25.

Assumptions of linear regression model.

A1. Linearity: $y = X\beta + \varepsilon$

A2. Full rank of X : $\text{rank}(X) = k$ ($n > k$)

A3. Exogeneity: $E[\varepsilon_i | X] = 0$ for $i=1, \dots, n$

$$\Rightarrow E[\varepsilon | X] = 0, \quad E(\varepsilon) = 0, \quad \text{Cov}(\varepsilon, X) = 0.$$

$$\Rightarrow E[y | X] = X\beta \quad (\text{with A1}).$$

A4. Homoskedasticity : $\text{Var}[\varepsilon_i | X] = \sigma^2$ for $i=1, \dots, n$.

Non-autocorrelation : $\text{Cov}[\varepsilon_i, \varepsilon_j | X] = 0$ for $i \neq j$.

$$E[\varepsilon \varepsilon' | X] = \begin{bmatrix} E[\varepsilon_1 \varepsilon_1 | X] & E[\varepsilon_1 \varepsilon_2 | X] & \dots & E[\varepsilon_1 \varepsilon_n | X] \\ \vdots & \vdots & \ddots & \vdots \\ E[\varepsilon_n \varepsilon_1 | X] & E[\varepsilon_n \varepsilon_2 | X] & \dots & E[\varepsilon_n \varepsilon_n | X] \end{bmatrix}$$

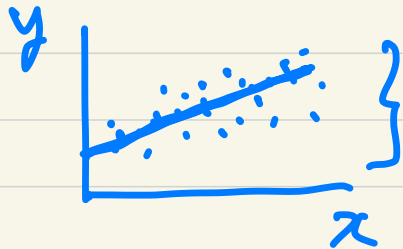
σ^2 $\varepsilon_t, \varepsilon_s$ σ^2

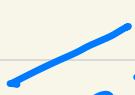
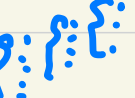
$$= \begin{bmatrix} \sigma^2 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \sigma^2 \end{bmatrix} = \sigma^2 I$$

\Rightarrow A4 can be written as $E[\varepsilon \varepsilon' | X] = \sigma^2 I$.

Theorem B.4.

$$\text{Var}[y] = \text{Var}_x[E[y|x]] + E_x[\text{Var}[y|x]]$$



$\text{Var}[y] =$  右边第1项
 右边第2项.

$$\begin{aligned} \text{Var}[\mathbf{y}] &= \text{Var}_x[E[\mathbf{y}|\mathbf{X}]] + E_x[\text{Var}[\mathbf{y}|\mathbf{X}]] \\ &= \text{Var}_x[E[\mathbf{y}|\mathbf{X}]] + E_x[E[\mathbf{y}\mathbf{y}'|\mathbf{X}] - \underbrace{E[\mathbf{y}|\mathbf{X}]}_{=0} \underbrace{E[\mathbf{y}'|\mathbf{X}]}_{=0}] \\ &= 0 + E_x[E[\mathbf{y}\mathbf{y}'|\mathbf{X}]] \\ &= E[\sigma^2 \mathbf{I}] = \sigma^2 \mathbf{I} \end{aligned}$$

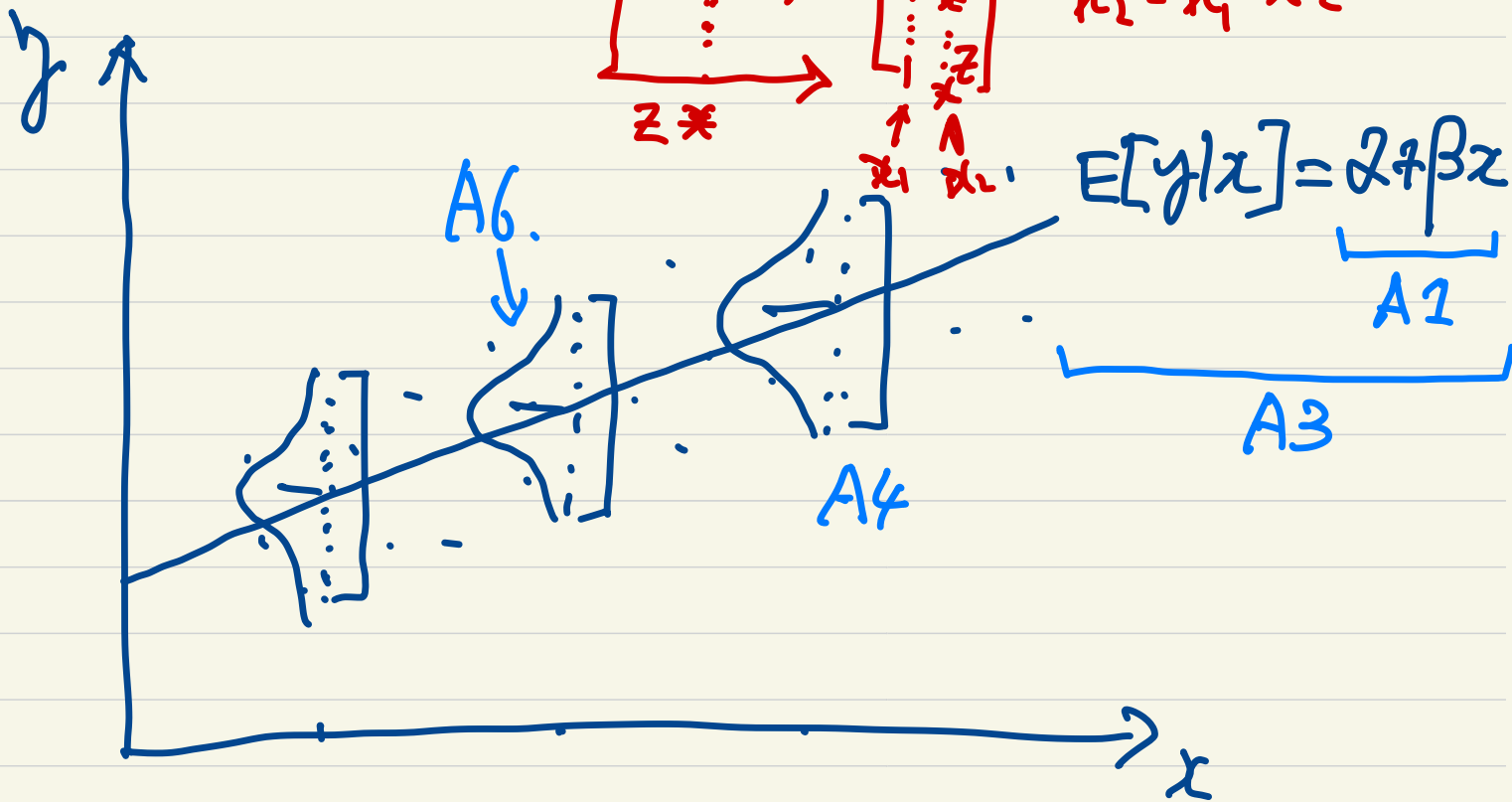
$E[\mathbf{y}\mathbf{y}'] - \mu\mu'$

A5. Data generation: X may be fixed or random.

Fixed: from experiments. $E[\varepsilon|X] = E[\varepsilon] = 0$
 $\text{Var}[\varepsilon] = \sigma^2 I$.

Random: observational data. $\overset{A3}{\downarrow}$ $\overset{A4}{\downarrow}$

A6. Normality: $\varepsilon|X \sim N[\overset{\downarrow}{0}, \sigma^2 I]$



About independence.

- (I) . Statistical independence : $f(x, y) = f_x(x) \cdot f_y(y)$.
- (II) . Uncorrelatedness : $\text{Cov}(x, y) = 0$.
- (III) . Mean independence : $E[y|x]$ does not depend on x .

. Linear independence : $X = [x_1, \dots, x_k]$

x_1, \dots, x_k are not linearly dependent

$$x_1 \neq \alpha_2 x_2 + \dots + \alpha_k x_k.$$

$$(I) \Rightarrow (II) \Rightarrow (III)$$

$\nLeftarrow \quad \nLeftarrow$

$$\underset{\substack{\uparrow \\ \text{known.}}}{y} = \underset{\substack{\uparrow \\ \text{known.}}}{X} \underset{\substack{\uparrow \\ \text{calculate } \beta}}{\beta} + \underset{=}{\varepsilon}$$

Model fitting.

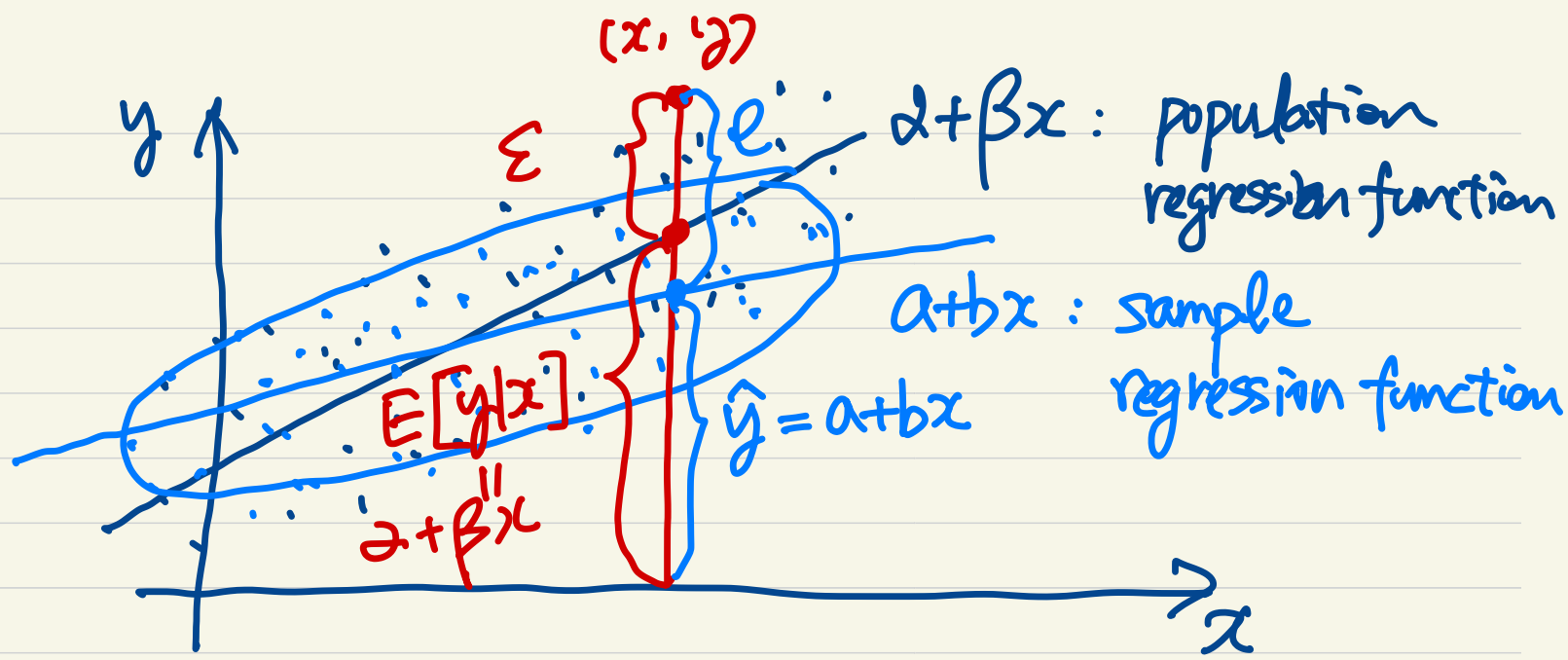
$$\rightarrow y_i = \hat{y}_i + e_i \\ = x_i' \beta + e_i$$

- Population regression function. *unknown*

$$E[y_i | x_i] = x_i' \beta, \quad (\varepsilon_i) = y_i - x_i' \beta.$$

- Sample regression function

$$\hat{y}_i = x_i' \underset{\text{known.}}{\beta} \quad \textcircled{e_i} = y_i - \hat{y}_i \quad \text{residual.}$$



(y_i, x_i) is known. $\beta = \begin{bmatrix} \alpha \\ \beta \end{bmatrix}$ is unknown.
 for $i = 1, \dots, n$. $b = \begin{bmatrix} a \\ b \end{bmatrix}$ is obtained from $[y, X]$.

Least Squares.

- The least squares fitting criterion.

$$\min_{b_0} S(b_0) = \underline{e_0' e_0} = (y - Xb_0)' (y - Xb_0).$$

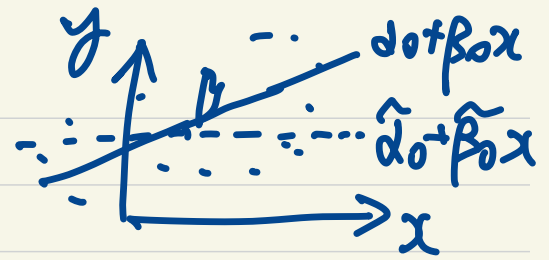
where $\underline{e_0} = y - \underline{Xb_0}$. $\underline{e_0' e_0} = [e_{0,1} \dots e_{0,n}] \begin{bmatrix} e_{0,1} \\ \vdots \\ e_{0,n} \end{bmatrix}$

Sum of squared residuals.

$$= \sum_{i=1}^n e_{0,i}^2$$

$$b = \underset{b_0}{\operatorname{argmin}} S(b_0)$$

$$y = Xb_0 + e_0$$



$$X = [x_1, \dots, x_k]$$

$$Xb_0 = [x_1, \dots, x_k] \begin{bmatrix} b_{0,1} \\ \vdots \\ b_{0,k} \end{bmatrix} = \sum_{m=1}^k x_m \cdot b_{0,m}$$

