

Estatística 2 - Lista 2

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26/07/21

① a) (3.4) We have that $X'\hat{e} =$
 $X'(y - X\hat{\beta}) = X'y - X'X(X'X)^{-1}X'y = 0$.
Thus, in particular, since $X = [X_1 \ X_2]$,
 $X_2'\hat{e} = 0$;

$X_2 = X\Gamma$, where $\Gamma = [\Theta \ I]'$, and
 I is an identity matrix with the same
dimension as the number of columns of X_2 .
So, $X_2'(y - X\hat{\beta}) = \Gamma'X'(y - X\hat{\beta}) = \Gamma\Theta = 0$.

b) (3.5) Let $\hat{e} = X\hat{\psi} + \hat{\mu}$ be the
regression model. We have that

$$\begin{aligned}\hat{\psi} &= (X'X)^{-1}X'\hat{e} = (X'X)^{-1}X'(y - X\hat{\beta}) = \\ &= (X'X)^{-1}X'(y - X(X'X)^{-1}X'y) = \\ &= (X'X)^{-1}X'y - (X'X)^{-1}X'y = 0\end{aligned}$$

where $\hat{\beta}$ is the coefficient vector from
the regression on y on X .

c) (3.50) $P = X(X'X)^{-1}X'$

$$P_i = X_i(X_i'X_i)^{-1}X_i' \quad i=1,2.$$

Now, $X'X = \begin{bmatrix} X_1' \\ X_2' \end{bmatrix} \begin{bmatrix} X_1 & X_2 \end{bmatrix} = \begin{bmatrix} X_1'X_1 & X_1'X_2 \\ X_2'X_1 & X_2'X_2 \end{bmatrix} =$
 $\begin{bmatrix} X_1'X_1 & 0 \\ 0 & X_2'X_2 \end{bmatrix}$, thus, $(X'X)^{-1} = \begin{bmatrix} (X_1'X_1)^{-1} & 0 \\ 0 & (X_2'X_2)^{-1} \end{bmatrix}$

$$\text{and } P = [X_1 \ X_2] \begin{bmatrix} (X_1' X_1)^{-1} & 0 \\ 0 & (X_2' X_2)^{-1} \end{bmatrix} \begin{bmatrix} X_1' \\ X_2' \end{bmatrix} = \\ = X_1 (X_1' X_1)^{-1} X_1' + X_2 (X_2' X_2)^{-1} X_2' = P_1 + P_2$$

d) (3.12) The first equation (3.53) cannot be estimated by OLS. See that if, define $X = [1 \ d_1 \ d_2]$ and $\beta = (\mu \ \alpha_1 \ \alpha_2)'$, we can rewrite 3.5.3 as

$$y = X\beta + e$$

However, $(X'X)$ is not invertible, since $d_2 = (-1)(d_1 - 1)$, i.e., X does not have full rank. Thus, $\hat{\beta}$ is not well-defined in this model.

The last two equations can be estimated since $X_1 = [d_1 \ d_2]$ and $X_2 = [1 \ d_1]$ have full rank.

(i) The equation (3.55) is more general, since it includes an intercept and d_1 and d_2 convey the same information.

Note that, in (3.54)

$$E(y_i | d_{1i} = 0) = E(y_i | d_{2i} = 1) = \alpha_2, \\ E(y_i | d_{1i} = 1) = E(y_i | d_{2i} = 0) = \alpha_1$$

and in (3.55)

$$E(y_i | d_{1i} = 0) = \mu, \\ E(y_i | d_{1i} = 1) = \mu + \phi,$$

$$\text{so } \alpha_2 = \mu, \\ \alpha_1 = \mu + \phi$$

$$(ii) \sum_{i=1}^n d_1 = n_1 \quad \text{and} \quad \sum_{i=1}^n d_2 = n_2$$

(iii) Letting $\alpha = (\alpha_1, \alpha_2)'$ and $X = [d_1 \ d_2]$, $y = X\alpha + e$.

The OLS estimator is

$$\hat{\alpha} = (X'X)^{-1}X'y = (\sum_{i=1}^n x_i'x_i)^{-1}(\sum_{i=1}^n x_i'y_i) =$$

$$= (\sum_{i=1}^n x_i'x_i)^{-1}(\sum_{i=1}^n x_i'(X\alpha + e)) = \alpha + (\sum_{i=1}^n x_i'x_i)^{-1}(\sum_{i=1}^n x_i'e_i)$$

If $E(x_i e_i) = 0$, as $n \rightarrow \infty$, $(\sum_{i=1}^n x_i'x_i)^{-1} \xrightarrow{p} E(x_i x_i')$
and $(\sum_{i=1}^n x_i'e_i) \xrightarrow{p} E(x_i e_i) = 0$, so
 $\hat{\alpha} \xrightarrow{p} \alpha$

e) (3.16) See that

$$\hat{e}'\hat{e} = \min_{\beta_1, \beta_2} (y - X_1\beta_1 - X_2\beta_2)'(y - X_1\beta_1 - X_2\beta_2)$$

$$\text{and } \tilde{e}'\tilde{e} = \min_{\beta_1} (y - X_1\beta_1)'(y - X_1\beta_1)$$

$$= \min_{\beta_1, \beta_2=0} (y - X_1\beta_1 - X_2\beta_2)'(y - X_1\beta_1 - X_2\beta_2)$$

Since $\tilde{e}'\tilde{e}$ is the restricted minimum,
 $\tilde{e}'\tilde{e} \geq \hat{e}'\hat{e}$

Now, from the definition of R^2_1

$$R^2_1 = 1 - \frac{\tilde{e}'\tilde{e}}{(y - \bar{y})(y - \bar{y})} \leq 1 - \frac{\hat{e}'\hat{e}}{(y - \bar{y})(y - \bar{y})} = R^2_2.$$

Moreover, $R^2_1 = R^2_2 \Leftrightarrow \tilde{e}'\tilde{e} = \hat{e}'\hat{e} \Leftrightarrow \hat{\beta}_2 = 0$

② Let $y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$, $\beta = \begin{pmatrix} \alpha \\ \beta_1 \\ \beta_2 \end{pmatrix}$, $e = \begin{pmatrix} e_1 \\ \vdots \\ e_n \end{pmatrix}$, and

$X = \begin{pmatrix} 1_n & x_1 & x_2 \end{pmatrix}$. Thus, the model can be written as $y = X\beta + e$ and the OLS estimator of β is $\hat{\beta} = (X'X)^{-1}X'y$ with residuals $\hat{e} = y - X\hat{\beta}$.

a) If $y - 1_n \bar{y}$ is substituted for y , the new estimator will be

$$\hat{\beta}_2 = (X'X)^{-1}X'(y - 1_n \bar{y}) = \hat{\beta} - (X'X)^{-1}X'1_n \bar{y}$$

As $X = \begin{pmatrix} 1_n & x_1 & x_2 \end{pmatrix}$, $1_n = X \begin{pmatrix} 1 & 0 & 0 \end{pmatrix}'$. Thus,

$$\hat{\beta}_2 = \hat{\beta} - (X'X)^{-1}X'X \begin{pmatrix} 1 & 0 & 0 \end{pmatrix}' \bar{y} = \hat{\beta} - \begin{pmatrix} \bar{y} \\ 0 \\ 0 \end{pmatrix}$$

$$= \begin{pmatrix} \hat{\alpha} - \bar{y} \\ \hat{\beta}_1 \\ \hat{\beta}_2 \end{pmatrix}$$

The residuals are

$$\begin{aligned} \hat{e}_2 &= y - 1_n \bar{y} - X \hat{\beta}_2 = y - 1_n \bar{y} - X(\hat{\beta} - \begin{pmatrix} 1 & 0 & 0 \end{pmatrix}' \bar{y}) \\ &= \hat{e} - (1_n - X \begin{pmatrix} 1 & 0 & 0 \end{pmatrix}') \bar{y} = \hat{e} \end{aligned}$$

b) If we use σy instead of y ,

$$\hat{\beta}_b = (X'X)^{-1}X'\sigma y = \sigma \hat{\beta} = \begin{pmatrix} \sigma \hat{\alpha} \\ \sigma \hat{\beta}_1 \\ \sigma \hat{\beta}_2 \end{pmatrix}$$

and $\hat{e}_b = \sigma y - X \hat{\beta}_b = \sigma y - \sigma X \hat{\beta} = \sigma \hat{e}$.

c) If we use $X_c = (1 \ \sigma x_1 \ x_2)$ instead of X ,

$$\hat{\beta}_c = (X_c' X_c)^{-1} X_c' y$$

See that $X_c = X \begin{bmatrix} 1 & 0 & 0 \\ 0 & \sigma & 0 \\ 0 & 0 & 1 \end{bmatrix} = X \Gamma$ where

$$\Gamma = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \sigma & 0 \\ 0 & 0 & 1 \end{bmatrix} \text{ . Thus,}$$

$$\begin{aligned} \hat{\beta}_c &= (\Gamma' X' X \Gamma)^{-1} \Gamma' X' y \\ &= \Gamma^{-1} (X' X)^{-1} \Gamma^{-1} \Gamma y \\ &= \Gamma^{-1} \hat{\beta} \\ &= \begin{pmatrix} \hat{\alpha} \\ \hat{\beta}_1 / \sigma \\ \hat{\beta}_2 \end{pmatrix} \end{aligned}$$

$$\text{and } \hat{e}_c = y - X_c \hat{\beta}_c = y - X \Gamma \Gamma^{-1} \hat{\beta} = \hat{e}$$

③ e) For each $j \in \{1, \dots, 5\}$, let $G_{i,j} = G_{i,1}, \dots, G_{i,j-1}, G_{i,j+1}, \dots, G_{i,5}$, i.e., the variables different from j .

For $j = 1, \dots, 4$

$$E(y_i | x_i, G_{i,j} = 1, G_{i,-j} = 0) = w_j + \lambda_j x_i \quad \text{and}$$

$$E(y_i | x_i, G_{i,j} = 1, G_{i,-j} = 0) = \beta_0 + \beta_1 x_i + \delta_j + \alpha_j x_i$$

Since this holds for all x_i ,

$$w_j = \beta_0 + \delta_j$$

$$\delta_j = w_j - \beta_0$$

$$\lambda_j = \beta_1 + \alpha_j$$

$$\Rightarrow \alpha_j = \lambda_j - \beta_1 \quad \forall j = 1, \dots, 4$$

For $j = 5$, $G_{i,j} = 0 \quad \forall j = 1, \dots, 4$, thus,

$$E(y_i | x_i, G_{i,5} = 1, G_{i,-5} = 0) = w_5 + \lambda_5 x_i \quad \text{and}$$

$$E(y_i | x_i, G_{i,5} = 1, G_{i,-5} = 0) = \beta_0 + \beta_1 x_i$$

Thus, $\beta_0 = w_5$ and $\beta_1 = \lambda_5$, and

$$\delta_j = w_j - w_5 \quad \text{and} \quad \alpha_j = \lambda_j - \lambda_5 \quad \forall j = 1, \dots, 4$$