

COMM8102 ECONOMETRIC ANALYSIS

ASSIGNMENT 1

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Excercise 2.4

$$\begin{aligned}\mathbb{E}[Y|X=0] &= 1 \cdot \mathbb{P}(Y=1|X=0) + 0 \cdot \mathbb{P}(Y=0|X=0) \\ &= 1 \cdot \frac{\mathbb{P}(Y=1, X=0)}{\mathbb{P}(X=0)} + 0 \cdot \frac{\mathbb{P}(Y=0, X=0)}{\mathbb{P}(X=0)} \\ &= 1 \cdot \frac{0.4}{0.4+0.1} + 0 \cdot \frac{0.1}{0.4+0.1} \\ &= 0.8\end{aligned}$$

$$\begin{aligned}\mathbb{E}[Y|X=1] &= 1 \cdot \mathbb{P}(Y=1|X=1) + 0 \cdot \mathbb{P}(Y=0|X=1) \\ &= 1 \cdot \frac{\mathbb{P}(Y=1, X=1)}{\mathbb{P}(X=1)} + 0 \cdot \frac{\mathbb{P}(Y=0, X=1)}{\mathbb{P}(X=1)} \\ &= 1 \cdot \frac{0.3}{0.3+0.2} + 0 \cdot \frac{0.2}{0.3+0.21} \\ &= 0.6\end{aligned}$$

$$\begin{aligned}
\mathbb{E}[Y^2|X=0] &= 1^2 \cdot \mathbb{P}(Y=1|X=0) + 0^2 \cdot \mathbb{P}(Y=0|X=0) \\
&= 1 \cdot \frac{\mathbb{P}(Y=1, X=0)}{\mathbb{P}(X=0)} + 0 \cdot \frac{\mathbb{P}(Y=0, X=0)}{\mathbb{P}(X=0)} \\
&= 1 \cdot \frac{0.4}{0.4+0.1} + 0 \cdot \frac{0.1}{0.4+0.1} \\
&= 0.8
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}[Y^2|X=1] &= 1^2 \cdot \mathbb{P}(Y=1|X=1) + 0^2 \cdot \mathbb{P}(Y=0|X=1), \\
&= 1 \cdot \frac{\mathbb{P}(Y=1, X=1)}{\mathbb{P}(X=1)} + 0 \cdot \frac{\mathbb{P}(Y=0, X=1)}{\mathbb{P}(X=1)}, \\
&= 1 \cdot \frac{0.3}{0.3+0.2} + 0 \cdot \frac{0.2}{0.3+0.21} \\
&= 0.6
\end{aligned}$$

$$\begin{aligned}
Var[Y|X=0] &= \mathbb{E}[Y^2|X=0] - (\mathbb{E}[Y|X=0])^2, \\
&= 0.8 - 0.8^2 \\
&= 0.16
\end{aligned}$$

$$\begin{aligned}
Var[Y|X=1] &= \mathbb{E}[Y^2|X=1] - (\mathbb{E}[Y|X=1])^2, \\
&= 0.6 - 0.6^2 \\
&= 0.24
\end{aligned}$$

Exercise 2.7

$$\begin{aligned}
\sigma(X) &= \text{Var}[Y|X] \\
&= \mathbb{E}[(Y - \mathbb{E}[Y|X])^2 | X] \\
&= \mathbb{E}[Y^2 + (\mathbb{E}[Y|X])^2 - 2 \cdot Y \cdot \mathbb{E}[Y|X] | X] \\
&= \mathbb{E}[Y^2 | X] + \mathbb{E}[(\mathbb{E}[Y|X])^2 | X] - 2 \cdot \mathbb{E}[Y \cdot \mathbb{E}[Y|X] | X] \\
&= \mathbb{E}[Y^2 | X] + (\mathbb{E}[Y|X])^2 - 2 \cdot \mathbb{E}[Y|X] \cdot \mathbb{E}[Y|X] \\
&= \mathbb{E}[Y^2 | X] - (\mathbb{E}[Y|X])^2
\end{aligned}$$

1 Exercise 2.18

(a)

$$\begin{aligned}
\mathbf{Q}_{XX} &= \mathbb{E}[XX^\top] \\
&= \begin{pmatrix} \mathbb{E}[1] & \mathbb{E}[X_2] & \mathbb{E}[X_3] \\ \mathbb{E}[X_2] & \mathbb{E}[X_2^2] & \mathbb{E}[X_2X_3] \\ \mathbb{E}[X_3] & \mathbb{E}[X_2X_3] & \mathbb{E}[X_3^2] \end{pmatrix} \\
&= \begin{pmatrix} 1 & \mathbb{E}[X_2] & \mathbb{E}[\alpha_1 + \alpha_2 X_2] \\ \mathbb{E}[X_2] & \mathbb{E}[X_2^2] & \mathbb{E}[\alpha_1 X_2 + \alpha_2 X_2^2] \\ \mathbb{E}[\alpha_1 + \alpha_2 X_2] & \mathbb{E}[\alpha_1 X_2 + \alpha_2 X_2^2] & \mathbb{E}[\alpha_1^2 + \alpha_2^2 X_2^2 + 2\alpha_1 \alpha_2 X_2] \end{pmatrix} \\
&= \begin{pmatrix} 1 & \mathbb{E}[X_2] & \alpha_1 + \alpha_2 \mathbb{E}[X_2] \\ \mathbb{E}[X_2] & \mathbb{E}[X_2^2] & \alpha_1 \mathbb{E}[X_2] + \alpha_2 \mathbb{E}[X_2^2] \\ \alpha_1 + \alpha_2 \mathbb{E}[X_2] & \alpha_1 \mathbb{E}[X_2] + \alpha_2 \mathbb{E}[X_2^2] & \alpha_1^2 + 2\alpha_1 \alpha_2 \mathbb{E}[X_2] + \alpha_2^2 \mathbb{E}[X_2^2] \end{pmatrix}.
\end{aligned}$$

Define

$$\begin{aligned}
\mathbf{v}_1 &= (1, \mathbb{E}[X_2], \alpha_1 + \alpha_2 \mathbb{E}[X_2])^\top, \\
\mathbf{v}_2 &= (\mathbb{E}[X_2], \mathbb{E}[X_2^2], \alpha_1 \mathbb{E}[X_2] + \alpha_2 \mathbb{E}[X_2^2])^\top, \\
\mathbf{v}_3 &= (\alpha_1 + \alpha_2 \mathbb{E}[X_2], \alpha_1 \mathbb{E}[X_2] + \alpha_2 \mathbb{E}[X_2^2], \alpha_1^2 + 2\alpha_1 \alpha_2 \mathbb{E}[X_2] + \alpha_2^2 \mathbb{E}[X_2^2])^\top.
\end{aligned}$$

$\mathbf{v}_1, \mathbf{v}_2$ and \mathbf{v}_3 are the first, second and third column of the matrix \mathbf{Q}_{XX} . We can observe that

$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 = \mathbf{v}_3.$$

By definition, $\mathbf{v}_1, \mathbf{v}_2$ and \mathbf{v}_3 are not linearly independent. Therefore, \mathbf{Q}_{XX} is not invertible.

(b)

Let $\mathcal{X} = (1, X_2)$, and $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$. As a result, $AX = \mathcal{X}$. Since X_3 is a linear function of X_2 , the best linear predictor $X^\top \beta_1 \equiv \mathcal{X}^\top \beta_2$ for different β_1 and β_2 . We also have

$$\begin{aligned} \beta_2 &= (\mathbb{E}[\mathcal{X}\mathcal{X}^\top])^{-1} \mathbb{E}[\mathcal{X}Y] \\ &= \begin{bmatrix} \mathbb{E}[1] & \mathbb{E}[X_2] \\ \mathbb{E}[X_2] & \mathbb{E}[X_2^2] \end{bmatrix}^{-1} \begin{bmatrix} \mathbb{E}[Y] \\ \mathbb{E}[X_2Y] \end{bmatrix} \\ &= \frac{1}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \begin{bmatrix} \mathbb{E}[X_2^2] & -\mathbb{E}[X_2] \\ -\mathbb{E}[X_2] & 1 \end{bmatrix} \begin{bmatrix} \mathbb{E}[Y] \\ \mathbb{E}[X_2Y] \end{bmatrix} \\ &= \frac{1}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \begin{bmatrix} \mathbb{E}[X_2^2] \mathbb{E}[Y] - \mathbb{E}[X_2] \mathbb{E}[X_2Y] \\ \mathbb{E}[X_2Y] - \mathbb{E}[X_2] \mathbb{E}[Y] \end{bmatrix} \\ &= \begin{bmatrix} \frac{\mathbb{E}[X_2^2] \mathbb{E}[Y] - \mathbb{E}[X_2] \mathbb{E}[X_2Y]}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \\ \frac{\mathbb{E}[X_2Y] - \mathbb{E}[X_2] \mathbb{E}[Y]}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \end{bmatrix} \end{aligned}$$

The best linear predictor of Y given X is

$$\begin{aligned} X^\top \beta_1 &= \mathcal{X}^\top \beta_2 \\ &= (AX)^\top \beta_2 \\ &= X^\top A^\top \begin{bmatrix} \frac{\mathbb{E}[X_2^2] \mathbb{E}[Y] - \mathbb{E}[X_2] \mathbb{E}[X_2Y]}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \\ \frac{\mathbb{E}[X_2Y] - \mathbb{E}[X_2] \mathbb{E}[Y]}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \end{bmatrix} \\ &= X^\top \begin{bmatrix} \frac{\mathbb{E}[X_2^2] \mathbb{E}[Y] - \mathbb{E}[X_2] \mathbb{E}[X_2Y]}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \\ \frac{\mathbb{E}[X_2Y] - \mathbb{E}[X_2] \mathbb{E}[Y]}{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2} \\ 0 \end{bmatrix} \end{aligned}$$

Exercise 3.3

$$\begin{aligned}
 X^\top \hat{\mathbf{e}} &= X^\top (Y - X\hat{\beta}) \\
 &= X^\top (Y - X(X^\top X)^{-1} X^\top Y) \\
 &= X^\top Y - \underbrace{X^\top X (X^\top X)^{-1} X^\top Y}_I \\
 &= X^\top Y - X^\top Y \\
 &= 0
 \end{aligned}$$

Exercise 3.12

Only (3.54) and (3.53) can be estimated by OLS. Since $\mathbf{D}_1 + \mathbf{D}_2 = \mathbf{1}_n$, there are perfect collinearity in (3.52), which violates the assumption of OLS. (3.52) has regressors $\mathbf{D}_1, \mathbf{D}_2$ and $\mathbf{1}_n$. (3.53) has regressors \mathbf{D}_1 and \mathbf{D}_2 . (3.53) has regressors \mathbf{D}_1 and $\mathbf{1}_n$.

$$\begin{aligned}
 a\mathbf{D}_1 + b\mathbf{D}_2 &= a\mathbf{D}_1 + b(\mathbf{1}_n - \mathbf{D}_1) \\
 &= (a - b)\mathbf{D}_1 + b\mathbf{1}_n = 0 \quad \text{if } a = b = 0
 \end{aligned}$$

\mathbf{D}_1 and \mathbf{D}_2 are linearly independent, but $\mathbf{D}_1, \mathbf{D}_2$ and $\mathbf{1}_n$ are linearly dependent.

(a)

No. \mathbf{D}_1 alone gives the same information as \mathbf{D}_1 and \mathbf{D}_2 .

For men, $\alpha_1 = \mu + \phi$. For women, $\alpha_2 = \mu$. So we have

$$\begin{aligned}
 \alpha_1 &= \mu + \phi \\
 \alpha_2 &= \mu
 \end{aligned}$$

or

$$\mu = \alpha_2$$

$$\phi = \alpha_1 - \alpha_2$$

(b)

The number of non-zero elements in \mathbf{D}_1 is the number of men and The number of non-zero elements in \mathbf{D}_2 is the number of women.

$$\mathbf{1}^\top \mathbf{D}_1 = n_1$$

$$\mathbf{1}^\top \mathbf{D}_2 = n_2$$

Excercise 3.19

$$\begin{aligned} \tilde{e}_i &= Y_i - \tilde{Y}_i \\ &= \frac{1}{1 - h_{ii}} \hat{e}_i \\ &= \frac{1}{1 - X_i (\mathbf{X}^\top \mathbf{X})^{-1} X_i} \hat{e}_i \\ &= \frac{1}{1 - \frac{1}{n}} \left(Y_i - X_i \hat{\beta} \right) \\ &= \frac{n}{n-1} \left(Y_i - \underbrace{X_i}_1 \left(\underbrace{\mathbf{X}^\top \mathbf{X}}_n \right)^{-1} \underbrace{\mathbf{X}^\top \mathbf{Y}}_{\sum Y_i} \right) \\ &= \frac{n}{n-1} (Y_i - \bar{Y}) \end{aligned}$$