

Ex 2.5 (a)

$$\begin{aligned}
 EPE(x_0) &= E_{y_0|x_0} E_{\tau}(y_0 - \hat{y}_0)^2 \\
 &= E_{y_0|x_0} E_{\tau}(y_0 - x_0^T \beta + x_0^T \beta - \hat{y}_0)^2 \quad (\text{trick}) \\
 &= E_{y_0|x_0} E_{\tau}^{(1)}(y_0 - x_0^T \beta)^2 + E_{y_0|x_0} E_{\tau}^{(2)}(x_0^T \beta - \hat{y}_0)^2 \\
 &\quad + E_{y_0|x_0} E_{\tau}^{(3)}[2(y_0 - x_0^T \beta)(x_0^T \beta - \hat{y}_0)]
 \end{aligned}$$

① Note for any point i we have $y_i = x_i^T \beta + \epsilon_i$
 $\Rightarrow y_0 - x_0^T \beta = \epsilon_0 \quad (*)$

$$\begin{aligned}
 E_{y_0|x_0} E_{\tau}(\epsilon_0)^2 &= \sigma^2 \xrightarrow{\text{using}} \Rightarrow E(\epsilon^2) = \text{Var}(\epsilon) + E(\epsilon)^2 \\
 &\Rightarrow E(\epsilon^2) = \sigma^2 + 0
 \end{aligned}$$

③ Again using (*) we get:

$$\begin{aligned}
 &2 E_{y_0|x_0} E_{\tau}[(\epsilon_0)(x_0^T \beta - \hat{y}_0)] \\
 &\quad \text{as } \epsilon \sim \text{iid} \\
 &\Rightarrow 2 E_{y_0|x_0} E_{\tau}(\epsilon_0) E_{y_0|x_0} E_{\tau}(x_0^T \beta - \hat{y}_0) = 0
 \end{aligned}$$

$$② E_{y_0|x_0} E_{\tau}(x_0^T \beta - \hat{y}_0)^2 = E_{\tau}(x_0^T \beta - \hat{y}_0)^2 \quad (\text{No dependence on } y_0)$$

$$= E_{\tau}(x_0^T \beta - E(\hat{y}_0) + E(\hat{y}_0) - \hat{y}_0)^2 \quad (\text{trick})$$

again split into 3 expressions:

$$= E_{\tau}(x_0^T \beta - E_{\tau}(\hat{y}_0))^2 + E_{\tau}(E_{\tau}(\hat{y}_0) - \hat{y}_0)^2 + 2 E_{\tau}[(x_0^T \beta - E_{\tau}(\hat{y}_0))(E_{\tau}(\hat{y}_0) - \hat{y}_0)] \quad \textcircled{c}$$

(a)
(b)

$$\begin{aligned}
 \textcircled{a} E_{\tau}(x_0^T \beta - E_{\tau}(\hat{y}_0))^2 \\
 &= (x_0^T \beta - E_{\tau}(\hat{y}_0))^2 \quad (\text{constant}) \\
 \text{Note: } x_0^T \beta &= E_{\tau}(\hat{y}_0) \quad (**) \\
 &= 0
 \end{aligned}$$

③ Again using (**) we find:

$$\begin{aligned}
 &2 E_{\tau}[(x_0^T \beta - E_{\tau}(\hat{y}_0))(E_{\tau}(\hat{y}_0) - \hat{y}_0)] \\
 &= 0
 \end{aligned}$$

$$\begin{aligned}
\textcircled{6} \quad & E_{\tau}(E_{\tau}(\hat{y}_0) - \hat{y}_0)^2 \\
&= \text{Var}_{\tau}(\hat{y}_0) \quad (\text{by definition of Variance}) \\
&= \text{Var}_{\tau}(x_0^T \hat{\beta}) \\
&= x_0^T \text{Var}_{\tau}(\hat{\beta}) x_0 \\
&= x_0^T (X^T X)^{-1} \sigma^2 x_0 \quad (\text{using 3-8})
\end{aligned}$$

and in order to drop the assumption that the x_i are fixed (non-random) we simply replace with the expectation.

$$= x_0^T E_{\tau}[(X^T X)^{-1}] x_0 \sigma^2$$

Now Putting all the pieces together we obtain that:

$$\begin{aligned}
EPE(x_0) &= E_{x_0} E_{\tau}(y_0 - \hat{y}_0)^2 \\
&= \sigma^2 + x_0^T E_{\tau}[(X^T X)^{-1}] x_0 \sigma^2
\end{aligned}$$

Ex 2.5 (b)

Given $EPE(x_0) = \sigma^2 + E x_0^T (X^T X)^{-1} x_0 \sigma^2$

We wish to find $E_{x_0} EPE(x_0)$

Assuming $E(X) = 0$ then $X^T X \rightarrow N \text{Cov}(X)$

$$\Rightarrow E_{x_0} EPE(x_0) = \sigma^2 + \frac{E_{x_0} x_0^T \text{Cov}(X)^{-1} x_0}{N} \sigma^2$$

Now, we are told that we wish to get this equation in terms of the trace. Thus we will use the identity:

$$E(B^T A B) = \text{trace}(A \text{Cov}(B)) + E(B)^T A E(B)$$

Here $A = P \times P$ and $B = P \times 1$ dimensions

Now,

$$E_{x_0} EPE(x_0) = \sigma^2 + [\text{trace}(\text{Cov}(X)^{-1} \text{Cov}(x_0)) + E(x_0)^T \text{Cov}(X)^{-1} E(x_0)] \sigma^2 / N$$

as $E(x_0) = 0$

$$= \sigma^2 + \text{trace}(\text{Cov}(X)^{-1} \text{Cov}(x_0)) \sigma^2 / N$$

$$= \sigma^2 + \text{trace}(I_P) \sigma^2 / N$$

$$= \sigma^2 + \frac{P \sigma^2}{N}$$