

Econometrics 710
Midterm Exam
March 4, 2015
Sample Answers

1. By expanding the square

$$\begin{aligned} T(\theta) &= E \left[(y - x'\theta)^2 \tau(x) \right] \\ &= E \left[y^2 \tau(x) \right] - 2E \left[yx'\tau(x) \right] \theta + \theta' E \left[xx'\tau(x) \right] \theta \end{aligned}$$

Taking the first derivative

$$\frac{\partial}{\partial \theta} T(\theta) = 2E \left[xy\tau(x) \right] \theta + 2E \left[xx'\tau(x) \right] \theta$$

Setting it equal to zero and solving for θ

$$\theta = (E \left[xx'\tau(x) \right])^{-1} E \left[xy\tau(x) \right]$$

2. Since $e = y - x'\theta$,

$$\begin{aligned} E \left[xe\tau(x) \right] &= E \left[xy\tau(x) \right] - E \left[xx'\tau(x) \right] \theta \\ &= E \left[xy\tau(x) \right] - E \left[xx'\tau(x) \right] (E \left[xx'\tau(x) \right])^{-1} E \left[xy\tau(x) \right] \\ &= E \left[xy\tau(x) \right] - E \left[xy\tau(x) \right] \\ &= 0 \end{aligned}$$

For this result, you do not need an additional assumption. For example, $E(e|x) = 0$ is not needed.

3. If the conditional mean is linear $E(y|x) = x'\beta$ then

$$\begin{aligned} \theta &= (E \left[xx'\tau(x) \right])^{-1} E \left(E \left[yx\tau(x)|x \right] \right) \\ &= (E \left[xx'\tau(x) \right])^{-1} E \left(x\tau(x)E \left[y|x \right] \right) \\ &= (E \left[xx'\tau(x) \right])^{-1} E \left(x\tau(x)x'\beta \right) \\ &= \beta \end{aligned}$$

so that $\theta = \beta$. When the conditional mean is linear it equals the best linear predictor, and thus θ equals the best linear predictor as well.

A common answer was: “When $\tau(x) = \tau$ is independent of x ”. This may appear to be technically correct, for then indeed the problem reduces to that of the best linear predictor. However, this is an uninteresting solution and thus I graded it as a missed answer. I tried to exclude this answer by including the explicit warning “Under what condition other than $\tau(x) = 1 \dots$ ”

4. $\hat{\theta} = (\sum_{i=1}^n x_i x_i' \tau(x_i))^{-1} \sum_{i=1}^n x_i y_i \tau(x_i)$. Alternatively, $\hat{\theta} = (X'TX)^{-1} (X'TY)$ where $T = \text{diag}\{\tau(x_i)\}$

5. If $E(e|x) = 0$ then $E(Y|X) = X\theta$ and

$$\begin{aligned} E(\hat{\theta}|X) &= (X'TX)^{-1} (X'TE(Y|X)) \\ &= (X'TX)^{-1} (X'TX\theta) \\ &= \theta \end{aligned}$$

By iterated expectations, $E(\hat{\theta}) = E(E(\hat{\theta}|X)) = \theta$ and $\hat{\theta}$ is unbiased for θ . Thus the estimator is unbiased when the conditional mean is linear.

6. By the WLLN,

$$\frac{1}{n} \sum_{i=1}^n x_i x_i' \tau(x_i) \rightarrow_p E(x_i x_i' \tau(x_i))$$

and

$$\frac{1}{n} \sum_{i=1}^n x_i y_i \tau(x_i) \rightarrow_p E(x_i y_i \tau(x_i))$$

By the continuous mapping theorem,

$$\begin{aligned}\hat{\theta} &= \left(\sum_{i=1}^n x_i x_i' \tau(x_i) \right)^{-1} \sum_{i=1}^n x_i y_i \tau(x_i) \\ &\xrightarrow{p} (E(x_i x_i' \tau(x_i)))^{-1} E(x_i y_i \tau(x_i)) \\ &= \theta\end{aligned}$$

and thus $\hat{\theta}$ is consistent for θ .

Regularity conditions sufficient for this result are:

- $E \|x_i\|^2 < \infty$
- $E y_i^2 < \infty$
- $E(x_i x_i' \tau(x_i)) > 0$

7. Since $y = X\theta + e$, then

$$\begin{aligned}\hat{\theta} &= (X'TX)^{-1} (X'Ty) \\ &= (X'TX)^{-1} (X'TX)\theta + (X'TX)^{-1} (X'Te) \\ &= \theta + (X'TX)^{-1} (X'Te).\end{aligned}$$

Then

$$\begin{aligned}\sqrt{n}(\hat{\theta} - \theta) &= \sqrt{n}(X'TX)^{-1} (X'Te) \\ &= \left(\frac{1}{n} \sum_{i=1}^n x_i x_i' \tau(x_i) \right)^{-1} \left(\frac{1}{\sqrt{n}} \sum_{i=1}^n x_i e_i \tau(x_i) \right)\end{aligned}$$

As shown in question 2, $E[x_i e_i \tau(x_i)] = 0$. By the CLT

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n x_i e_i \tau(x_i) \rightarrow_d N(0, S)$$

where $S = E(x_i x_i' e_i^2 \tau(x_i)^2)$. Then

$$\sqrt{n}(\hat{\theta} - \theta) \rightarrow_d Q^{-1}N(0, S) = N(0, Q^{-1}SQ^{-1})$$

where $Q = E(x_i x_i' \tau(x_i))$.

Regularity conditions sufficient for this result are:

- $E \|x_i\|^4 < \infty$
- $E y_i^4 < \infty$
- $E(x_i x_i' \tau(x_i)) > 0$

8. If $E(e^2|x) = \sigma^2$ then $S = E(x_i x_i' e_i^2 \tau(x_i)^2) = \tilde{Q}\sigma^2$ where $\tilde{Q} = E(x_i x_i' \tau(x_i)^2)$. Then $Q^{-1}SQ^{-1} = Q^{-1}\tilde{Q}Q^{-1}\sigma^2$ and the asymptotic distribution is $N(0, Q^{-1}\tilde{Q}Q^{-1}\sigma^2)$.

9. $\hat{V} = \left(\frac{1}{n} \sum_{i=1}^n x_i x_i' \tau(x_i) \right)^{-1} \left(\frac{1}{n} \sum_{i=1}^n x_i x_i' \tau(x_i)^2 \hat{e}_i^2 \right) \left(\frac{1}{n} \sum_{i=1}^n x_i x_i' \tau(x_i) \right)^{-1}$ where $\hat{e}_i = y_i - x_i' \hat{\theta}$.