

# Problem Set 10

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## Problem 1

(a) To pin down  $\beta$ , we have

$$\begin{aligned}\frac{1}{T} \sum_{t=1}^T y_{it} &= u_i + \left( \frac{1}{T} \sum_{t=1}^T x'_{it} \right) \beta + \frac{1}{T} \sum_{t=1}^T e_{it} \\ y_{it} - \frac{1}{T} \sum_{t=1}^T y_{it} &= \left( x'_{it} - \frac{1}{T} \sum_{t=1}^T x'_{it} \right) \beta + e_{it} - \frac{1}{T} \sum_{t=1}^T e_{it} \\ \left( y_{it} - \frac{1}{T} \sum_{t=1}^T y_{it} \right) - \left( x'_{it} - \frac{1}{T} \sum_{t=1}^T x'_{it} \right) \beta &= e_{it} - \frac{1}{T} \sum_{t=1}^T e_{it}\end{aligned}$$

Since  $E[e_{it}|x_{i1}, x_{i2}, \dots] = 0$ , we get  $E[x_{is}e_{it}] = 0$ , and hence

$$\begin{aligned}E \left[ \left( x_{it} - \frac{1}{T} \sum_{t=1}^T x_{it} \right) \left( \left( y_{it} - \frac{1}{T} \sum_{t=1}^T y_{it} \right) - \left( x'_{it} - \frac{1}{T} \sum_{t=1}^T x'_{it} \right) \beta \right) \right] \\ = E \left[ \left( x_{it} - \frac{1}{T} \sum_{t=1}^T x_{it} \right) \left( e_{it} - \frac{1}{T} \sum_{t=1}^T e_{it} \right) \right] = 0\end{aligned}$$

For  $\mu_u$ , we have

$$\begin{aligned}E \left[ \frac{1}{T} \sum_{t=1}^T (y_{it} - x'_{it}\beta) - \mu_u \right] &= E \left[ \frac{1}{T} \sum_{t=1}^T (u_i + e_{it}) - \mu_u \right] \\ &= E \left[ u_i + \frac{1}{T} \sum_{t=1}^T e_{it} - \mu_u \right] = \mu_u + 0 - \mu_u = 0\end{aligned}$$

For  $\mu_{ux}$ , we get

$$\begin{aligned}E \left[ \frac{1}{T} \sum_{t=1}^T x_{it} (y_{it} - x'_{it}\beta) - \mu_{ux} \right] &= E \left[ \frac{1}{T} \sum_{t=1}^T x_{it} (u_i + e_{it}) - \mu_{ux} \right] \\ &= E \left[ \frac{1}{T} \sum_{t=1}^T x_{it} u_i + \frac{1}{T} \sum_{t=1}^T x_{it} e_{it} - \mu_{ux} \right] = \mu_{ux} + 0 - \mu_{ux} = 0\end{aligned}$$

Lastly, for  $\sigma_u^2$ , we note that

$$\begin{aligned}
E \left[ \frac{1}{\binom{T}{2}} \sum_{s \neq t \in \{1, 2, \dots, T\}} (y_{is} - x'_{is}\beta)(y_{it} - x'_{it}\beta) - \mu_u^2 - \sigma_u^2 \right] &= E \left[ \frac{1}{\binom{T}{2}} \sum_{s \neq t \in \{1, 2, \dots, T\}} (u_i + e_{is})(u_i + e_{it}) - \mu_u^2 - \sigma_u^2 \right] \\
&= E \left[ \frac{1}{\binom{T}{2}} \sum_{s \neq t \in \{1, 2, \dots, T\}} (u_i^2 + e_{is}u_i + e_{it}u_i + e_{is}e_{it}) - \mu_u^2 - \sigma_u^2 \right] \\
&= E \left[ u_i^2 + \frac{1}{\binom{T}{2}} \sum_{s \neq t \in \{1, 2, \dots, T\}} (e_{is}u_i + e_{it}u_i + e_{is}e_{it}) - \mu_u^2 - \sigma_u^2 \right] = E[u_i^2] - \mu_u^2 - \sigma_u^2 = \sigma_u^2 - \sigma_u^2 = 0
\end{aligned}$$

So altogether:

$$g(x_i, y_i, \beta, \mu_u, \mu_{ux}, \sigma_u^2) = \begin{bmatrix} \left( x_{it} - \frac{1}{T} \sum_{t=1}^T x_{it} \right) \left( \left( y_{it} - \frac{1}{T} \sum_{t=1}^T y_{it} \right) - \left( x'_{it} - \frac{1}{T} \sum_{t=1}^T x'_{it} \right) \beta \right) \\ \frac{1}{T} \sum_{t=1}^T (y_{it} - x'_{it}\beta) - \mu_u \\ \frac{1}{T} \sum_{t=1}^T x_{it}(y_{it} - x'_{it}\beta) - \mu_{ux} \\ \frac{1}{\binom{T}{2}} \sum_{s \neq t \in \{1, 2, \dots, T\}} (y_{is} - x'_{is}\beta)(y_{it} - x'_{it}\beta) - \mu_u^2 - \sigma_u^2 \end{bmatrix}$$

And we will have a unique solution as long as

$$\left( x_{it} - \frac{1}{T} \sum_{t=1}^T x_{it} \right) \left( x'_{it} - \frac{1}{T} \sum_{t=1}^T x'_{it} \right)$$

is invertible.

(b) We have that

$$\begin{aligned}
E \left[ \prod_{t=1}^l y_{it} \right] &= E \left[ \prod_{t=1}^l (u_i + e_{it}) \right] \\
&= E \left[ \prod_{t=1}^l u_i \right]
\end{aligned}$$

since  $E[e_{it}|u_i, \dots, e_{is}, s \neq t] = 0$ . Hence a consistent estimator is

$$\frac{1}{n} \sum_{i=1}^n \left( \prod_{t=1}^l y_{it} \right)$$

We need  $T \geq l$ .

## Problem 2

We have

$$f(y_{it}|u, \sigma^2) = \frac{1}{\sigma} \phi \left( \frac{y_{it} - u_i}{\sigma} \right)$$

So the log-likelihood is

$$\begin{aligned} l(\mu, \sigma^2) &= \sum_{i=1}^n \sum_{t=1}^2 \left( \log \phi \left( \frac{y_{it} - u_i}{\sigma} \right) - \log \sigma \right) \\ &= \sum_{i=1}^n \sum_{t=1}^2 \left( -\frac{1}{2} \left( \frac{y_{it} - u_i}{\sigma} \right)^2 - \frac{1}{2} \log(2\pi) - \frac{1}{2} \log \sigma^2 \right) \end{aligned}$$

Taking the FOCs,

$$\begin{aligned} \frac{\partial l}{\partial u_i} &= - \sum_{t=1}^2 \left( \frac{y_{it} - u_i}{\sigma} \right) = 0 \\ \sum_{t=1}^2 y_{it} - 2u_i &= 0 \\ \hat{u}_i &= \frac{y_{i1} + y_{i2}}{2} \end{aligned}$$

and

$$\begin{aligned} \frac{\partial l}{\partial \sigma^2} &= \sum_{i=1}^n \sum_{t=1}^2 \left( \frac{1}{2} \left( \frac{(y_{it} - u_i)^2}{(\sigma^2)^2} \right) - \frac{1}{2} \frac{1}{\sigma^2} \right) = 0 \\ \sum_{i=1}^n \sum_{t=1}^2 ((y_{it} - u_i)^2) - 2n\sigma^2 &= 0 \\ \hat{\sigma}^2 &= \frac{1}{2n} \sum_{i=1}^n \sum_{t=1}^2 ((y_{it} - u_i)^2) \\ &= \frac{1}{2n} \sum_{i=1}^n \sum_{t=1}^2 \left( y_{it} - \frac{y_{i1} + y_{i2}}{2} \right)^2 \\ &= \frac{1}{2n} \sum_{i=1}^n \left( \frac{y_{i1} - y_{i2}}{2} \right)^2 + \left( \frac{y_{i1} - y_{i2}}{2} \right)^2 \\ &= \frac{1}{n} \sum_{i=1}^n \left( \frac{y_{i1} - y_{i2}}{2} \right)^2 \\ &= \frac{1}{4n} \sum_{i=1}^n (y_{i1} - y_{i2})^2 \end{aligned}$$

This probability limit is

$$\begin{aligned} \hat{\sigma}^2 &= \frac{1}{4} \left( \frac{1}{n} (y_{i1} - y_{i2})^2 \right) \rightarrow_p \frac{1}{4} E(y_{i1} - y_{i2})^2 \\ &= \frac{1}{4} E(e_{i1} - e_{i2})^2 = \frac{1}{4} (2\sigma^2) = \frac{1}{2} \sigma^2 \end{aligned}$$