

Econometrics HW7

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EX 1

Solution We consider the fixed effects regression model,

$$Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it} \quad (1)$$

And we use the binary variables to develop the fix effects regression model, which is given by:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \gamma_2 D2_i + \gamma_3 D3_i + \dots + \gamma_n Dn_i + u_{it}, \quad (2)$$

where the binary variable $D1_i$ is omitted.

Therefore we have:

(a) For entity 1 in time period 1, namely $i = 1, t = 1$, the regression model becomes

$$Y_{11} = \beta_0 + \beta_1 X_{11},$$

where $slope = \beta_1$ and $intercept = \beta_0$.

(b) For entity 1 in time period 3, namely $i = 1, t = 3$, the regression model becomes

$$Y_{13} = \beta_0 + \beta_1 X_{13},$$

where $slope = \beta_1$ and $intercept = \beta_0$.

(c) For entity 3 in time period 1, namely $i = 3, t = 1$, the regression model becomes

$$Y_{31} = \beta_0 + \beta_1 X_{31} + \gamma_3,$$

where $slope = \beta_1$ and $intercept = \beta_0 + \gamma_3$.

(d) For entity 3 in time period 3, namely $i = 3, t = 3$, the regression model becomes

$$Y_{33} = \beta_0 + \beta_1 X_{33} + \gamma_3,$$

where $slope = \beta_1$ and $intercept = \beta_0 + \gamma_3$.

Next we consider the time fixed effects regression model:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \delta_B 2_t + \dots + \delta_T B T_t + u_{it}, \quad (3)$$

where the binary variable $B1_t$ is omitted.

Therefore we have:

(a) For entity 1 in time period 1, namely $i = 1, t = 1$, the regression model becomes

$$Y_{11} = \beta_0 + \beta_1 X_{11},$$

where $slope = \beta_1$ and $intercept = \beta_0$.

(b) For entity 1 in time period 3, namely $i = 1, t = 3$, the regression model becomes

$$Y_{13} = \beta_0 + \beta_1 X_{13} + \delta_3,$$

where $slope = \beta_1$ and $intercept = \beta_0 + \delta_3$.

(c) For entity 3 in time period 1, namely $i = 3, t = 1$, the regression model becomes

$$Y_{31} = \beta_0 + \beta_1 X_{31},$$

where $slope = \beta_1$ and $intercept = \beta_0$.

(d) For entity 3 in time period 3, namely $i = 3, t = 3$, the regression model becomes

$$Y_{33} = \beta_0 + \beta_1 X_{33} + \delta_3,$$

where $slope = \beta_1$ and $intercept = \beta_0 + \delta_3$.

Finally we consider the entity and time fixed effects regression model:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \gamma_2 D2_i + \dots + \gamma_n Dn_i + \delta_B 2_t + \dots + \delta_T BT_t + u_{it}. \quad (4)$$

(a) For entity 1 in time period 1, namely $i = 1, t = 1$, the regression model becomes

$$Y_{11} = \beta_0 + \beta_1 X_{11},$$

where $slope = \beta_1$ and $intercept = \beta_0$.

(b) For entity 1 in time period 3, namely $i = 1, t = 3$, the regression model becomes

$$Y_{13} = \beta_0 + \beta_1 X_{13} + \delta_3,$$

where $slope = \beta_1$ and $intercept = \beta_0 + \delta_3$.

(c) For entity 3 in time period 1, namely $i = 3, t = 1$, the regression model becomes

$$Y_{31} = \beta_0 + \beta_1 X_{31} + \gamma_3,$$

where $slope = \beta_1$ and $intercept = \beta_0 + \gamma_3$.

(d) For entity 3 in time period 3, namely $i = 3, t = 3$, the regression model becomes

$$Y_{33} = \beta_0 + \beta_1 X_{33} + \gamma_3 + \delta_3,$$

where $slope = \beta_1$ and $intercept = \beta_0 + \gamma_3 + \delta_3$.

EX 2

Solution (a) For the fixed entity effects model (1), we consider the least square estimator of α_i , we minimize the objective function:

$$\sum_t \sum_i u_{it}^2 = \sum_t \sum_i (Y_{it} - \alpha_i D1_i - \alpha_2 D2_i - \dots - \alpha_n Dn_i)^2.$$

By the FOC condition we have,

$$\frac{\partial}{\partial \alpha_j} \sum_t \sum_i (Y_{it} - \alpha_i D1_i - \alpha_2 D2_i - \dots - \alpha_n Dn_i)^2 = 0, \quad j = 1, 2, \dots, n.$$

Specially for α_1 , we have

$$\begin{aligned}
& \frac{\partial}{\partial \alpha_1} \sum_t \sum_i (Y_{it} - \alpha_1 D1_i - \alpha_2 D2_i - \dots - \alpha_n Dn_i)^2 \\
&= \sum_t \sum_i \frac{\partial}{\partial \alpha_1} (Y_{it} - \alpha_1 D1_i - \alpha_2 D2_i - \dots - \alpha_n Dn_i)^2 \\
&= \sum_t \sum_i -2D1_i (Y_{it} - \alpha_1 D1_i - \alpha_2 D2_i - \dots - \alpha_n Dn_i) \\
&= \sum_t -2(Y_{1t} - \alpha_1) = 0.
\end{aligned}$$

Therefore we have

$$\hat{\alpha}_1 = \frac{1}{T} \sum_{t=1}^T Y_{1t}.$$

Generally,

$$\hat{\alpha}_j = \frac{1}{T} \sum_{t=1}^T Y_{jt}, \quad j = 1, 2, \dots, n.$$

Given that T is fixed, the statistical property of α_j won't change, that is to say WLLN is invalid. Therefore, α_j is not consistent as $n \rightarrow \infty$ for all j .

(b) From (a), we know that

$$\hat{\alpha}_j = \frac{1}{T} \sum_{t=1}^T Y_{jt}, \quad j = 1, 2, \dots, n.$$

In the case that $T = 4$, the normal approximation from CLT is not likely to be valid, hence $\hat{\alpha}_j, j = 1, 2, \dots, n$ are not likely to be approximately normally distributed.

EX 3

Solution (a) For the fixed effects regression model

$$Y_{it} = \alpha_i + X'_{it}\beta + u_{it}, \quad (5)$$

we assume that the individual-specific effect α_i is correlated with X_{it} , which may cause the omitted variables which do not change over time. By letting $\bar{Y}_{i\cdot} = T^{-1} \sum_{t=1}^T Y_{it}$ and similarly for $\bar{X}_{i\cdot}$ and $\bar{u}_{i\cdot}$. Then we define $\tilde{Y}_{it} = Y_{it} - \bar{Y}_{i\cdot}$ and similarly for \tilde{X}_{it} and \tilde{u}_{it} . We have

$$\begin{aligned}
\bar{Y}_{i\cdot} &= \frac{1}{T} \sum_{t=1}^T Y_{it} \\
&= \frac{1}{T} \sum_{t=1}^T (\alpha_i + X'_{it}\beta + u_{it}) \\
&= \frac{1}{T} \left(\sum_{t=1}^T \alpha_i + \sum_{t=1}^T X'_{it}\beta + \sum_{t=1}^T u_{it} \right) \\
&= \alpha_i + \bar{X}'_{i\cdot}\beta + \bar{u}_{i\cdot}.
\end{aligned}$$

Then we have

$$\begin{aligned}
\tilde{Y}_{it} &= Y_{it} - \bar{Y}_{i\cdot} \\
&= \alpha_i + X'_{it}\beta + u_{it} - (\alpha_i + \bar{X}'_{i\cdot}\beta + \bar{u}_{i\cdot}) \\
&= \tilde{X}'_{it}\beta + \tilde{u}_{it}
\end{aligned}$$

(b) Then we consider the OLS estimator for the demeaned model by minimizing

$$\frac{1}{N} \frac{1}{T} \sum_i \sum_t \tilde{u}_{it}^2 = \frac{1}{N} \frac{1}{T} \sum_i \sum_t (\tilde{Y}_{it} - \tilde{X}'_{it} \beta)^2.$$

We have

$$\begin{aligned} \frac{d}{d\beta} \left(\frac{1}{N} \frac{1}{T} \sum_i \sum_t \tilde{u}_{it}^2 \right) &= \frac{d}{d\beta} \left[\frac{1}{N} \frac{1}{T} \sum_i \sum_t (\tilde{Y}_{it} - \tilde{X}'_{it} \beta)^2 \right] \\ &= \frac{1}{N} \frac{1}{T} \sum_i \sum_t \frac{d}{d\beta} (\tilde{Y}_{it} - \tilde{X}'_{it} \beta)^2 \\ &= \frac{1}{N} \frac{1}{T} \sum_i \sum_t 2(\tilde{Y}_{it} - \tilde{X}'_{it} \beta) \frac{d}{d\beta} (\tilde{Y}_{it} - \tilde{X}'_{it} \beta) \\ &= -2 \frac{1}{N} \frac{1}{T} \sum_i \sum_t \tilde{X}_{it} (\tilde{Y}_{it} - \tilde{X}'_{it} \beta) \\ &= -2 \frac{1}{N} \frac{1}{T} \tilde{X}' (\tilde{Y} - \tilde{X} \beta), \end{aligned}$$

where we have

$$\tilde{X} = \begin{pmatrix} \tilde{X}_{11} & \cdots & \tilde{X}_{1T} \\ \vdots & \ddots & \vdots \\ \tilde{X}_{N1} & \cdots & \tilde{X}_{NT} \end{pmatrix}, \tilde{Y} = \begin{pmatrix} \tilde{Y}_{11} & \cdots & \tilde{Y}_{1T} \\ \vdots & \ddots & \vdots \\ \tilde{Y}_{N1} & \cdots & \tilde{Y}_{NT} \end{pmatrix}$$

For FOC, namely $\frac{dSSR(\beta)}{d\beta} = 0$,

$$\begin{aligned} \tilde{X}' (\tilde{Y} - \tilde{X} \hat{\beta}^{FE}) &= 0 \\ \Rightarrow \tilde{X}' \tilde{Y} - (\tilde{X}' \tilde{X}) \hat{\beta}^{FE} &= 0 \\ \Rightarrow \hat{\beta}^{FE} &= (\tilde{X}' \tilde{X})^{-1} \tilde{X}' \tilde{Y}. \end{aligned}$$

And we have

$$\begin{aligned} \hat{\beta}^{FE} &= (\tilde{X}' \tilde{X})^{-1} \tilde{X}' \tilde{Y} \\ &= (\tilde{X}' \tilde{X})^{-1} \tilde{X}' (\tilde{X} \beta + \tilde{u}) \\ &= \beta + (\tilde{X}' \tilde{X})^{-1} \tilde{X}' \tilde{u} \\ &= \beta + \left(\frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \tilde{X}_{it} \tilde{X}'_{it} \right)^{-1} \left(\frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \tilde{X}_{it} \tilde{u}_{it} \right). \end{aligned}$$

(c) We notice that

$$\frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \tilde{X}_{it} \tilde{u}_{it} = \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}).$$

We assume that $\{Y_{it}, X'_{it}\}_{i=1}^N$ is an observable IID random sample. By WLLN for IID samples, we have as $N \rightarrow \infty$

$$\begin{aligned} &\frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}) \\ &\xrightarrow{p} \mathbb{E} \left[\frac{1}{T} \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}) \right] \\ &= \mathbb{E} \left[\mathbb{E} \left[\frac{1}{T} \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}) \middle| X_{i1}, \dots, X_{iT} \right] \right] \\ &= \frac{1}{T} \sum_{t=1}^T \mathbb{E} \left[(X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) \mathbb{E} [u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it} | X_{i1}, \dots, X_{iT}] \right] \neq 0. \end{aligned}$$

We can see that without the assumption of strict exogeneity, the FE estimator $\hat{\beta}^{FE}$ is not consistent.

(d) Under assumption of strict exogeneity, we have that as $N \rightarrow \infty$

$$\begin{aligned}
& \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}) \\
& \xrightarrow{p} \mathbb{E}[\frac{1}{T} \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it})] \\
& = \mathbb{E}[\mathbb{E}[\frac{1}{T} \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}) | X_{i1}, \dots, X_{iT}]] \\
& = \frac{1}{T} \sum_{t=1}^T \mathbb{E}[(X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) \mathbb{E}[u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it} | X_{i1}, \dots, X_{iT}]] \\
& = \frac{1}{T} \sum_{t=1}^T \mathbb{E}[(X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) \cdot 0] = 0.
\end{aligned}$$

Therefore, under assumption of strict exogeneity, the FE estimator $\hat{\beta}^{FE}$ is consistent.

(e) By the WLLN of IID samples and ergodic stationary processes (We assume that the observable stochastic process $\{Y_{it}, X'_{it}\}_{t=1}^T$ is jointly stationary and ergodic for all i), we have as $N, T \rightarrow \infty$

$$\begin{aligned}
& \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T (X_{it} - \frac{1}{T} \sum_{t=1}^T X_{it}) (u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}) \\
& \xrightarrow{p} \mathbb{E}[(X_{it} - \mathbb{E}[X_{it}]) (u_{it} - \mathbb{E}[u_{it}])] \\
& = Cov(X_{it}, u_{it}) = 0
\end{aligned}$$