

W2003 Final

Q1 is from 1999 MT

Q2 is related to HW questions

Q4 is asymptotic normality / consistency of OLS

Q3 - Binary choice model

• migrate or not

$$u_{i,p} = x_{i,p} \beta_p + \varepsilon_{i,p}$$

if stay

$$u_{i,m} = x_{i,m} \beta_m + \varepsilon_{i,m}$$

if migrate

$$c_i = z_i \lambda + u_i$$

(cost)

} want to estimate
 $\beta_p, \beta_m, \lambda$

$$\text{Let } y_i = \begin{cases} 1 & \text{if stay} \\ 0 & \text{if migrate} \end{cases}$$

$$\text{Will stay iff } u_{i,p} \geq u_{i,m} - c_i$$

$$\text{iff } x_{i,p} \beta_p + \varepsilon_{i,p} \geq x_{i,m} \beta_m + \varepsilon_{i,m} - z_i \lambda - u_i$$

$$\text{iff } x_{i,p} \beta_p - x_{i,m} \beta_m + z_i \lambda \geq -\varepsilon_{i,p} + \varepsilon_{i,m} - u_i$$

$$\text{By assumption, } \begin{bmatrix} \varepsilon_{i,p} \\ \varepsilon_{i,m} \\ u_i \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \Sigma \right) \text{ where } \Sigma = \begin{bmatrix} \sigma_{pp} & \sigma_{pm} & \sigma_{pu} \\ \sigma_{pm} & \sigma_{mm} & \sigma_{mu} \\ \sigma_{pu} & \sigma_{mu} & \sigma_{uu} \end{bmatrix}$$

$$\Rightarrow [-1 \quad 1 \quad -1] \begin{bmatrix} \varepsilon_{i,p} \\ \varepsilon_{i,m} \\ u_i \end{bmatrix} = \underbrace{-\varepsilon_{i,p} + \varepsilon_{i,m} - u_i}_{\equiv \eta_i} \sim N \left(0, \underbrace{[-1 \quad 1 \quad -1] \Sigma [-1 \quad 1 \quad -1]'}_{\Sigma^*} \right)$$

$$\text{where } \Sigma^* = [-1 \quad 1 \quad -1] \begin{bmatrix} \sigma_{pp} & \sigma_{pm} & \sigma_{pu} \\ \sigma_{pm} & \sigma_{mm} & \sigma_{mu} \\ \sigma_{pu} & \sigma_{mu} & \sigma_{uu} \end{bmatrix} \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix}$$

$$= [-\sigma_{pp} + \sigma_{pm} - \sigma_{pu} \quad -\sigma_{pm} + \sigma_{mm} - \sigma_{mu} \quad -\sigma_{pu} + \sigma_{mu} - \sigma_{uu}] \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix}$$

$$= \sigma_{pp} - \sigma_{pm} + \sigma_{pu} - \sigma_{pm} + \sigma_{mm} - \sigma_{mu} - \sigma_{pu} + \sigma_{mu} + \sigma_{uu}$$

$$= \sigma_{pp} - 2\sigma_{pm} - 2\sigma_{mu} + \sigma_{mm} + \sigma_{uu} \equiv \sigma^2$$

$$\begin{aligned}
 E[Y_i | X_{i,p}, X_{i,m}, Z_i] &= \Pr[Y_i = 1 | X_{i,p}, X_{i,m}, Z_i] \\
 &= \Pr[\eta_i < X_{i,p}\beta_p - X_{i,m}\beta_m + Z_i\gamma] \\
 &= \Pr\left[\frac{\eta_i}{\sigma} < \frac{X_{i,p}\beta_p - X_{i,m}\beta_m + Z_i\gamma}{\sigma}\right] \\
 &= \Phi\left(\frac{X_{i,p}\beta_p - X_{i,m}\beta_m + Z_i\gamma}{\sigma}\right)
 \end{aligned}$$

a) Probit model is

$$Y_i = \Phi\left(\frac{X_{i,p}\beta_p - X_{i,m}\beta_m + Z_i\gamma}{\sigma}\right) + v_i = \Phi\left(\frac{W_i\delta}{\sigma}\right) + v_i$$

$$\text{where } W_i = [X_{i,p} \quad -X_{i,m} \quad Z_i] \quad , \quad \delta = \begin{bmatrix} \beta_p \\ \beta_m \\ \gamma \end{bmatrix}$$

$$\text{and } v_i = Y_i - E[Y_i | W_i]$$

b) Construct the log-likelihood:

$$f(y_i | W_i) = \left[\Phi\left(\frac{W_i\delta}{\sigma}\right)\right]^{y_i} \left[1 - \Phi\left(\frac{W_i\delta}{\sigma}\right)\right]^{1-y_i}$$

$$\log L = \sum_{i=1}^n y_i \log \Phi\left(\frac{W_i\delta}{\sigma}\right) + \sum_{i=1}^n (1-y_i) \log \left[1 - \Phi\left(\frac{W_i\delta}{\sigma}\right)\right]$$

c) What is $\hat{\delta}^{MLE}$?

FOC:

$$(\delta): 0 = \sum_{i=1}^n y_i \frac{1}{\Phi\left(\frac{W_i\hat{\delta}^{MLE}}{\sigma}\right)} \varphi\left(\frac{W_i\hat{\delta}^{MLE}}{\sigma}\right) \cdot \frac{W_i'}{\sigma} + \sum_{i=1}^n (1-y_i) \frac{1}{1 - \Phi\left(\frac{W_i\hat{\delta}^{MLE}}{\sigma}\right)} \left(-\varphi\left(\frac{W_i\hat{\delta}^{MLE}}{\sigma}\right)\right) \frac{W_i'}{\sigma}$$

$\hat{\delta}^{MLE}$ solves (δ) .

But we might have an identification problem (if we don't know σ): we are estimating $\frac{\delta}{\sigma}$.

Weighted nonlinear least squares

Recall: $v_i = Y_i - E[Y_i | W_i]$

$$= \begin{cases} 1 - E[Y_i | W_i] & \text{if } Y_i = 1 \text{ w/prob } \Phi\left(\frac{W_i \delta}{\sigma}\right) \\ -E[Y_i | W_i] & \text{if } Y_i = 0 \text{ w/prob } 1 - \Phi\left(\frac{W_i \delta}{\sigma}\right) \end{cases}$$

$$\Rightarrow v(v_i | W_i) = \Phi\left(\frac{W_i \delta}{\sigma}\right) \left[1 - \Phi\left(\frac{W_i \delta}{\sigma}\right)\right]$$

Thus, we have

$$\hat{\delta}^{WNLs} = \underset{\delta}{\operatorname{argmin}} \sum_{i=1}^n \frac{\{Y_i - \Phi\left(\frac{W_i \delta}{\sigma}\right)\}^2}{\Phi\left(\frac{W_i \delta_0}{\sigma}\right) \left[1 - \Phi\left(\frac{W_i \delta_0}{\sigma}\right)\right]}$$

FOC:

$$(\delta): 0 = 2 \sum_{i=1}^n \frac{\{Y_i - \Phi\left(\frac{W_i \delta^{WNLs}}{\sigma}\right)\} (-\psi\left(\frac{W_i \delta^{WNLs}}{\sigma}\right)) \frac{W_i}{\sigma}}{\Phi\left(\frac{W_i \delta_0}{\sigma}\right) \left[1 - \Phi\left(\frac{W_i \delta_0}{\sigma}\right)\right]}$$

$\hat{\delta}^{WNLs}$ solves (δ)

- d) Discuss the asymptotic properties of these estimators
- Under regularity conditions, ML and WNLs are asymptotically normal and consistent.

$$\sqrt{n} (\hat{\delta}_{ML} - \delta_0) \xrightarrow{d} N(0, [I_1(\delta_0)]^{-1})$$

where $I_1(\delta_0) = \frac{1}{n} E \left[- \frac{\partial^2 \log L}{\partial \delta \partial \delta' \big|_{\delta_0}} \right] = \frac{1}{n} E \left[\frac{\partial}{\partial \delta} \left[\frac{-(Y_i - \Phi\left(\frac{W_i \delta}{\sigma}\right))}{\Phi\left(\frac{W_i \delta}{\sigma}\right) [1 - \Phi\left(\frac{W_i \delta}{\sigma}\right)]} \psi\left(\frac{W_i \delta}{\sigma}\right) \frac{W_i}{\sigma} \right] \bigg|_{\delta_0} \right]$

$= I_n(\delta_0)$ $s(W_i, \delta)$

$$= E \left[s(W_i, \delta_0) s(W_i, \delta_0)' \right]$$

$$= E \left[\left\{ \frac{Y_i - \Phi\left(\frac{W_i \delta_0}{\sigma}\right)}{\Phi\left(\frac{W_i \delta_0}{\sigma}\right) [1 - \Phi\left(\frac{W_i \delta_0}{\sigma}\right)]} \right\}^2 W_i' W_i \right]$$