

①

2009 Theory I #2

$$\text{2a. i)} \quad E[X] = E(E[X|\lambda]) = E[\lambda] = \theta^{-1}$$

$$E[Y] = E(E[Y|\lambda]) = E[\beta\lambda] = \frac{\beta}{\theta} \quad \text{I. #2}$$

$$\text{Var}[X] = E(\text{Var}[X|\lambda]) + \text{Var}(E[X|\lambda]) \\ = E[\lambda] + \text{Var}[\lambda] = \frac{1}{\theta} + \frac{1}{\theta^2}$$

$$\text{Var}[Y] = E(E[Y|\lambda]) + \text{Var}(E[Y|\lambda]) \\ = E[\beta\lambda] + \text{Var}[\beta\lambda] = \frac{\beta}{\theta} + \frac{\beta^2}{\theta^2}$$

$$\text{Cov}[X, Y] = E[(X - EX)(Y - EY)]$$

$$= E[XY] - (EX)(EY)$$

$$= E(E[XY|\lambda]) - (EX)(EY)$$

$$\stackrel{\text{def}}{=} E(E[X|\lambda]E[Y|\lambda]) - (EX)(EY)$$

$$= E(\lambda \cdot \beta\lambda) - (EX)(EY)$$

$$= \beta \left(\frac{1}{\theta^2} + \frac{1}{\theta^2} \right) - \frac{1}{\theta} \cdot \frac{\beta}{\theta} = \frac{\cancel{\theta}\cancel{\theta}+2\beta}{\theta^2} - \frac{\beta}{\theta^2}$$

$$= \frac{\beta}{\theta^2}$$

(2)

$$p_{x,y}(x,y) = \int p(x,y|\lambda) p(\lambda) d\lambda$$

$$= \int_0^\infty \frac{\lambda^x e^{-\lambda}}{x!} \cdot \frac{(\beta\lambda)^y e^{-\beta\lambda}}{y!} \theta e^{-\theta\lambda} d\lambda$$

$$= \frac{\beta^y \theta}{x! y!} \int_0^\infty \lambda^{x+y} e^{-(\theta+\beta+1)\lambda} d\lambda$$

$$= \frac{\beta^y \theta}{x! y!} \frac{\Gamma(x+y+1)}{(\beta+\theta+1)^{x+y+1}} = \frac{\theta}{\beta+\theta+1} \binom{x+y}{x} \left(\frac{1}{\beta+\theta+1}\right)^x \left(\frac{\beta}{\beta+\theta+1}\right)^y$$

2b)

$$l_n(\theta, \beta) = \bar{z} \left\{ \ln \theta - (x_i + y_i + 1) \log(\theta + \beta + 1) + y_i \log \beta + c(x_i, y_i) \right\}$$

$$\left\{ \begin{array}{l} \partial_\theta l_n(\theta, \beta) = \bar{z} \left\{ \frac{1}{\theta} - \frac{x_i + y_i + 1}{\theta + \beta + 1} \right\} = \frac{n}{\theta} - \frac{n(\bar{x}_n + \bar{y}_n + 1)}{\theta + \beta + 1} \stackrel{\text{set } 0}{=} 0 \\ \partial_\beta l_n(\theta, \beta) = \bar{z} \left\{ -\frac{x_i + y_i + 1}{\theta + \beta + 1} + \frac{y_i}{\beta} \right\} = -\frac{n(\bar{x}_n + \bar{y}_n + 1)}{\theta + \beta + 1} + \frac{n\bar{y}_n}{\beta} \stackrel{\text{set } 0}{=} 0 \end{array} \right.$$

$$\Rightarrow \left\{ \begin{array}{l} \hat{\theta}_n + \hat{\beta}_n + 1 - \hat{\theta}_n(\bar{x}_n + \bar{y}_n + 1) = 0 \\ \bar{y}_n(\hat{\theta}_n + \hat{\beta}_n + 1) - \hat{\beta}_n(\bar{x}_n + \bar{y}_n + 1) = 0 \end{array} \right.$$

$$\Rightarrow \left\{ \begin{array}{l} -(\bar{x}_n + \bar{y}_n)\hat{\theta}_n + \hat{\beta}_n = -1 \\ \bar{y}_n\hat{\theta}_n - (\bar{x}_n + 1)\hat{\beta}_n = -\bar{y}_n \end{array} \right. \Rightarrow \hat{\beta}_n = (\bar{x}_n + \bar{y}_n)\hat{\theta}_n - 1$$

$$\begin{aligned} \Rightarrow -\bar{y}_n &= \bar{y}_n\hat{\theta}_n - (\bar{x}_n + 1)[(\bar{x}_n + \bar{y}_n)\hat{\theta}_n - 1] \\ &= \bar{y}_n\hat{\theta}_n - [\bar{x}_n^2 + \bar{x}_n\bar{y}_n + \bar{x}_n + \bar{y}_n]\hat{\theta}_n + \bar{x}_n + 1 \\ &= -\bar{x}_n(\bar{x}_n + \bar{y}_n + 1)\hat{\theta}_n + \bar{x}_n + 1 \Rightarrow \hat{\theta}_n = \bar{x}_n^{-1} \end{aligned}$$

$$\Rightarrow \hat{\theta}_n = \frac{\bar{X}_n + \bar{Y}_n}{\bar{X}_n} + \hat{\beta}_n = -1$$

$$\Rightarrow \hat{\beta}_n = \frac{\bar{Y}_n + \bar{Y}_n}{\bar{X}_n} - 1 = \frac{\bar{Y}_n}{\bar{X}_n}$$

2c Under the conditions of Ferguson pg 121,

$$\sqrt{n} \begin{pmatrix} \hat{\theta}_n - \theta \\ \hat{\beta}_n - \beta \end{pmatrix} \xrightarrow{D} N(0, [I(\theta, \beta)]^{-1})$$

remains to obtain $[I(\theta, \beta)]^{-1}$

$$\partial_\theta^2 l(\theta, \beta) = -\frac{1}{\theta^2} + \frac{x+y+1}{(\theta+\beta+1)^2}$$

$$\partial_\beta^2 l(\theta, \beta) = -\frac{y}{\beta^2} + \frac{x+y+1}{(\theta+\beta+1)^2}$$

$$\partial_\theta \partial_\beta l(\theta, \beta) = \frac{x+y+1}{(\theta+\beta+1)^2}$$

$$B E\left[\frac{x+y+1}{(\theta+\beta+1)^2}\right] = \frac{\theta^{-1} + \beta\theta^{-1} + 1}{(\theta+\beta+1)^2} = \frac{\theta^{-1}(1+\beta+\theta)}{(\theta+\beta+1)^2} = \frac{1}{\theta(\theta+\beta+1)}$$

$$I(\theta, \beta) = \begin{bmatrix} \frac{1}{\theta^2} - \frac{1}{\theta(\theta+\beta+1)} & -\frac{1}{\theta(\theta+\beta+1)} \\ -\frac{1}{\theta(\theta+\beta+1)} & \frac{1}{\beta\theta} - \frac{1}{\theta(\theta+\beta+1)} \end{bmatrix}$$

$$= \frac{1}{\beta\theta^2(\theta+\beta+1)} \begin{bmatrix} \beta(\theta+\beta+1) - \beta\theta & -\beta\theta \\ -\beta\theta & \theta(\theta+\beta+1) - \beta\theta \end{bmatrix}$$

$$= \frac{1}{\beta\theta^2(\theta+\beta+1)} \begin{bmatrix} \beta(\beta+1) & -\beta\theta \\ -\beta\theta & \theta(\theta+1) \end{bmatrix}$$

$$[I(\theta, \beta)]^{-1} = \frac{\beta\theta^2(\theta+\beta+1)}{\beta(\beta+1)\theta(\theta+1) - (-\beta\theta)^2} \begin{bmatrix} \theta(\theta+1) & \beta\theta \\ \beta\theta & \beta(\beta+1) \end{bmatrix} \quad (4)$$

$$\boxed{\begin{aligned} \beta(\beta+1)\theta(\theta+1) - \beta^2\theta^2 &= \beta^2\theta(\theta+1) + \beta\theta(\theta+1) - \beta^2\theta^2 \\ &= \beta^2\theta^2 + \beta^2\theta + \beta\theta^2 + \beta\theta - \beta^2\theta^2 = \beta^2\theta + \beta\theta^2 + \beta\theta = \beta\theta(\beta+\theta+1) \end{aligned}}$$

$$= \theta \begin{bmatrix} \theta(\theta+1) & \beta\theta \\ \beta\theta & \beta(\beta+1) \end{bmatrix} = \begin{bmatrix} \theta^2(\theta+1) & \beta\theta^2 \\ \beta\theta^2 & \theta\beta(\beta+1) \end{bmatrix}$$

↙

$$\boxed{2d.i} \quad T_2 = \sqrt{n} \bar{X}_n / 2 \left(\frac{\bar{X}_n}{\bar{X}_n} - 1 \right) = \sqrt{n} \left(\sqrt{\frac{\bar{X}_n}{2}} \left(\frac{\bar{X}_n}{\bar{X}_n} - 1 \right) \right)$$

$$= \sqrt{n} \left((2\hat{\theta}_n)^{-1/2} (\hat{\beta}_n - 1) \right) = \sqrt{n} \left(g(\hat{\theta}_n, \hat{\beta}_n) \right)$$

where $g(a, b) = (2a)^{-1/2} (b - 1)$. Now

$$g(\theta, 1) = 0, \quad \frac{\partial}{\partial a} g(a, b) = \frac{-1}{2(b-1)} \left[-\frac{1}{2} a^{-3/2} \right] = -(2a)^{-3/2} (b-1)$$

$$\frac{\partial}{\partial b} g(a, b) = (2a)^{-1/2}, \quad \text{Let } \bar{Z} = [I(\theta, 1)]^{-1} = \begin{bmatrix} * & * \\ * & 2\theta \end{bmatrix}$$

so that by the delta method

$$\begin{aligned} \text{if } T_2 &= \sqrt{n} \left(g(\hat{\theta}_n, \hat{\beta}_n) - g(\theta, \beta) \right) \xrightarrow{D} N(0, \dot{g}(\theta, 1) \bar{Z} [\dot{g}(\theta, 1)]') \\ &\stackrel{D}{=} N(0, (2\theta)^{-1} 2\theta) \stackrel{D}{=} N(0, 1) \end{aligned}$$

2d.ii

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{D} N(0, \theta^2(\theta+1))$$

$$\text{Let } g(x) = \frac{1}{x}, \quad \dot{g}(x) = -\frac{1}{x^2}$$

$$\Rightarrow \sqrt{n}(\hat{\theta}_n^{-1} - \theta^{-1}) \stackrel{D}{=} \sqrt{n}(g(\hat{\theta}_n^{-1}) - g(\theta)) \rightarrow \\ N(0, [\dot{g}(\theta)]^2 \theta^2(\theta+1)) \stackrel{D}{=} N(0, \theta+1)$$

~~thus~~ ~~As tending to zero~~ $\Rightarrow \sqrt{n}\hat{\theta}_n^{-1} = O_p(1)$

$$T_2 - T_2 = \sqrt{n} \left[\frac{1}{2\hat{\theta}_n} (\hat{\beta}_n - 1 + \log \hat{\beta}_n) \right]$$

$$\begin{pmatrix} \bar{x}_n \\ \bar{y}_n \end{pmatrix} \xrightarrow{P} \begin{pmatrix} \theta^{-1} \\ \beta\theta^{-1} \end{pmatrix} \text{ by SLLN so that by CMT}$$

$$\hat{\beta}_n = \frac{\bar{y}_n}{\bar{x}_n} \xrightarrow{P} \frac{\beta\theta^{-1}}{\theta^{-1}} = \beta$$

Furthermore by ~~arguing about~~ the CMT we obtain (under H_0)

~~As tending to zero~~ and ~~log tends to zero~~

$$\hat{\beta}_n - 1 + \log \hat{\beta}_n \xrightarrow{P} 1 - 1 + \log(1) = 0$$

Thus,

$$T_2 - T_2 = O_p(1) O_p(1) = O_p(1)$$

2d.iii. Immediate

from Slutsky's thm.

Still need (e)!