

2015, Part 1

7/10/17

#3

a) We know $E\begin{bmatrix} X_i \\ Y_i \end{bmatrix} = \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}$ are identifiable (b/c of Golden Rule of estimability/identifiability).

All params of $\begin{Bmatrix} R_i \\ R_i Y_i \\ R_i X_i \end{Bmatrix}$ are estimable (b/c we have the joint likelihood & all data is observed)

$$E[R_i Y_i] = E[R_i] E[Y_i] = \pi \mu_y \quad \checkmark$$

$$E[R_i X_i] = E[R_i] E[X_i] = \pi \mu_x \quad \checkmark$$

$$\text{Var}(R_i Y_i) = E[R_i^2 Y_i^2] - (E[R_i] E[Y_i])^2$$

$$= E[R_i] E[Y_i^2] - \pi^2 \mu_y^2$$

$$= \pi (\text{Var}(Y_i) + (E[Y_i])^2) - \pi^2 \mu_y^2$$

$$= \pi (\sigma_{22} + \mu_y^2) - \pi^2 \mu_y^2 = \pi \mu_y^2 (1 - \pi) + \pi \sigma_{22}$$

We know (since this is the obs. data vector) that we can get all expectations, variances, & covariances of the RVs (R_i , $R_i Y_i$, & $R_i X_i$) in this vector

known/identifiable \Rightarrow identifiable \checkmark

$$\text{Var}(R_i X_i) = \dots = \pi \mu_x^2 (1 - \pi) + \pi \sigma_{11} \quad \Rightarrow \text{identifiable}$$

(same process)

$$\text{Cov}(R_i Y_i, R_i X_i) = E[R_i^2 Y_i X_i] - \underbrace{E[R_i Y_i]}_{\pi \mu_y} \underbrace{E[R_i X_i]}_{\pi \mu_x}$$

$$= E[R_i] E[Y_i X_i] - \pi^2 \mu_y \mu_x$$

$$= \pi (\text{Cov}(X_i, Y_i) + E[Y_i] E[X_i]) - \pi^2 \mu_y \mu_x$$

$$= \pi (\sigma_{12} + \mu_y \mu_x) - \pi^2 \mu_y \mu_x$$

only unknown here \Rightarrow identifiable.