

Chapter 13
Random effects

Stat 566
 4-15-24
 ①

$$y_{ij} = \mu + \tau_i + \varepsilon_{ij} \quad \begin{matrix} i=1, \dots, a \\ j=1, \dots, n \end{matrix}$$

$$\begin{aligned} E[\varepsilon_{ij}] &\equiv 0 & \tau_i \text{'s are random variables} \\ V[\varepsilon_{ij}] &= \sigma^2 & E[\tau_i] &\equiv 0 & \text{All of the } \varepsilon_{ij} \text{'s and} \\ & & V[\tau_i] &\equiv \sigma_\tau^2 & \tau_i \text{'s are independent} \end{aligned}$$

$$\begin{aligned} H_0: \sigma_\tau^2 &= 0 \\ H_1: \sigma_\tau^2 &> 0 \end{aligned}$$

Decomposition of sum of squares

②

$$\begin{aligned} SS_{TOT} &= SS_{TRT} + SS_{E} \\ \sum_{i=1}^a \sum_{j=1}^n (y_{ij} - \bar{y}_{..})^2 &= n \sum_{i=1}^a (\bar{y}_{i.} - \bar{y}_{..})^2 + \sum_{i,j} (y_{ij} - \bar{y}_{i.})^2 \end{aligned}$$

$$\text{Find } E[SS_{TRT}] = n E\left[\sum_{i=1}^a (\bar{y}_{i.} - \bar{y}_{..})^2\right]$$

$$= n E\left[\sum_{i=1}^a \bar{y}_{i.}^2 - 2\bar{y}_{..} \sum_{i=1}^a \bar{y}_{i.} + a\bar{y}_{..}^2\right]$$

$$= n E\left[\sum_{i=1}^a \bar{y}_{i.}^2 - a\bar{y}_{..}^2\right] \quad \begin{cases} \text{let } E[\bar{y}_{i.}^2] = C_i \\ \text{let } E[\bar{y}_{..}^2] = D \end{cases}$$

(3)

$$C_i: y_{ij} = \mu + \tau_i + \varepsilon_{ij}$$

$$\bar{y}_{i.} = \mu + \tau_i + \bar{\varepsilon}_{i.}$$

$$\bar{y}_{i.}^2 = \mu^2 + \tau_i^2 + \bar{\varepsilon}_{i.}^2 + 2\mu\tau_i + 2\mu\bar{\varepsilon}_{i.} + 2\tau_i\bar{\varepsilon}_{i.}$$

$$C_i = E[\bar{y}_{i.}^2] = \mu^2 + \underbrace{E[\tau_i^2]}_{\substack{\text{"} \\ V[\tau_i] + (E[\tau_i])^2 \\ \sigma_\tau^2 + 0}} + \underbrace{E[\bar{\varepsilon}_{i.}^2]}_{\substack{V[\bar{\varepsilon}_{i.}] + (E[\bar{\varepsilon}_{i.}])^2 \\ \frac{\sigma^2}{n} + 0}} + 0 + 0 + 0$$

$$C_i = \mu^2 + \sigma_\tau^2 + \frac{\sigma^2}{n}$$

(4)

$$D: y_{ij} = \mu + \tau_i + \varepsilon_{ij}$$

$$\bar{y}_{..} = \mu + \bar{\tau}_{..} + \bar{\varepsilon}_{..}$$

$$\bar{y}_{..}^2 = \mu^2 + \bar{\tau}_{..}^2 + \bar{\varepsilon}_{..}^2 + 2\mu\bar{\tau}_{..} + 2\mu\bar{\varepsilon}_{..} + 2\bar{\tau}_{..}\bar{\varepsilon}_{..}$$

$$D = E[\bar{y}_{..}^2] = \mu^2 + E[\bar{\tau}_{..}^2] + E[\bar{\varepsilon}_{..}^2] + 0 + 0 + 0$$

$$= \mu^2 + \frac{\sigma_\tau^2}{a} + \frac{\sigma^2}{an}$$

$$\text{Now } E[SS_{TRT}] = n \left[\sum_{i=1}^a C_i - aD \right]$$

$$= n \left[a \left(\mu^2 + \sigma_\tau^2 + \frac{\sigma^2}{n} \right) - a \left(\mu^2 + \frac{\sigma_\tau^2}{a} + \frac{\sigma^2}{an} \right) \right]$$

$$= n \left[(a-1)\sigma_{\tau}^2 + \sigma^2 \left(\frac{a}{n} - \frac{1}{n} \right) \right]$$

(5)

$$= (a-1) [n\sigma_{\tau}^2 + \sigma^2] = E[SS_{\text{TRT}}]$$

Define $MS_{\text{TRT}} = \frac{SS_{\text{TRT}}}{a-1}$

Then $E[MS_{\text{TRT}}] = n\sigma_{\tau}^2 + \sigma^2$

Under $H_0: \sigma_{\tau}^2 = 0$, $E[MS_{\text{TRT}}] = \sigma^2$

Recall: In the fixed effects model,

$$E[MS_{\text{TRT}}] = n \frac{\sum_{i=1}^a \tau_i^2}{a-1} + \sigma^2$$

Facts (require normality assumption on all τ_i 's and ε_{ij} 's) (6)

1. $\frac{SSE}{\sigma^2} \sim \chi^2_{N-a}$ ($N=na$)

2. $\frac{SS_{\text{TRT}}}{\sigma^2} \sim \chi^2_{a-1}$

3. SSE and SS_{TRT} are independent

\Rightarrow Under H_0 , $\frac{\frac{SS_{\text{TRT}}}{\sigma^2} / (a-1)}{\frac{SSE}{\sigma^2} / (N-a)} = \frac{MS_{\text{TRT}}}{MS_E} \sim F_{a-1, N-a}$

So there is no difference in the F test for
a 1-way ANOVA with fixed vs. random effects.

(7)

Suppose H_0 is rejected and you wish to estimate σ^2_{τ}

$$E[MS_{\text{TET}}] = n\sigma^2_{\tau} + \sigma^2$$

$$E[MS_E] = \sigma^2$$

$$E\left[\frac{MS_{\text{TET}} - MS_E}{n}\right] = \sigma^2_{\tau}$$

So an unbiased estimator of σ^2_{τ} is $\hat{\sigma}^2_{\tau} = \frac{MS_{\text{TET}} - MS_E}{n}$

$\hat{\sigma}^2_{\tau}$ doesn't have a known distribution.

(8)

Consider $\frac{\sigma^2_{\tau}}{\sigma^2 + \sigma^2_{\tau}}$

$$y_{ij} = \mu + \tau_i + \epsilon_{ij}$$

$$V(y_{ij}) = \sigma^2_{\tau} + \sigma^2$$

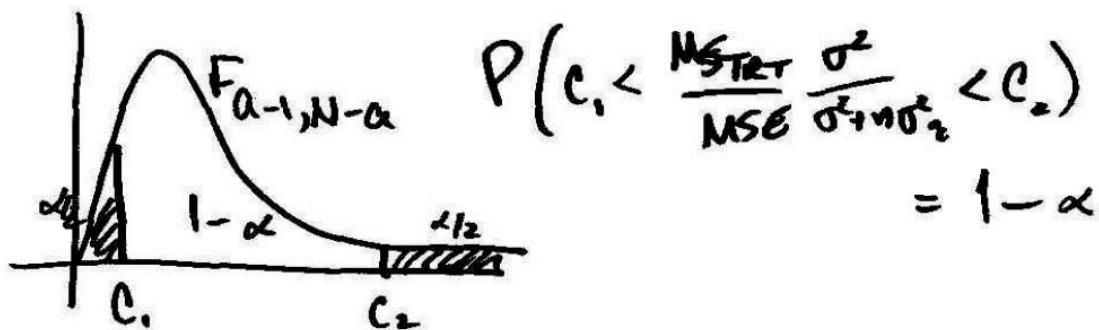
This is the proportion of the variance of y_{ij}
that is explained by the factor.

We know: Under H_0 , $\frac{SS_{\text{TET}}}{\sigma^2} \sim \chi^2_{a-1}$

Under either H_0 or H_1 , $\frac{SS_E}{\sigma^2} \sim \chi^2_{N-a}$

Fact: Under H_1 , $\frac{SS_{TRT}}{\sigma^2 + n\sigma_e^2} \sim \chi^2_{a-1}$ (9)

$$\frac{\frac{SS_{TRT}}{\sigma^2 + n\sigma_e^2} / (a-1)}{\frac{SSE}{\sigma^2} / (N-a)} = \frac{MS_{TRT}}{MSE} \frac{\sigma^2}{\sigma^2 + n\sigma_e^2} \sim F_{a-1, N-a}$$



$$c_1 \underbrace{\frac{MSE}{MS_{TRT}}}_{b_1} < \frac{\sigma^2}{\sigma^2 + n\sigma_e^2} < c_2 \underbrace{\frac{MSE}{MS_{TRT}}}_{b_2} \quad \text{with } 1-\alpha \text{ confidence}$$

$$\frac{1}{b_1} > \frac{\sigma^2 + n\sigma_e^2}{\sigma^2} > \frac{1}{b_2}$$

$$\underbrace{\frac{1}{b_1} - 1}_{d_1} > \frac{\sigma_e^2}{\sigma^2} > \underbrace{\frac{1}{b_2} - 1}_{d_2}$$

(41)

$$d_1 > \frac{\sigma_2^2}{\sigma^2} > d_2$$

$$f(d_1) > f\left(\frac{\sigma_2^2}{\sigma^2}\right) > f(d_2) \text{ if } f \text{ is } \uparrow$$

$$\frac{d_1}{1+d_1} > \frac{\frac{\sigma_2^2}{\sigma^2}}{1+\frac{\sigma_2^2}{\sigma^2}} > \frac{d_2}{1+d_2}$$
$$\frac{d_1}{1+d_1} > \frac{\sigma_2^2}{\sigma^2 + \sigma_2^2} > \frac{d_2}{1+d_2}$$

Consider $f(x) = \frac{x}{1+x}$

