

**M3/M4S3 STATISTICAL THEORY II**  
**THE JOINT DISTRIBUTION OF THE SAMPLE QUANTILES**

**RESULT 1:** If  $Y_1, Y_2, \dots, Y_{n+1} \sim \text{Exponential}(1)$  are independent random variables, and  $S_1, S_2, \dots, S_{n+1}$  are defined by

$$S_k = \sum_{j=1}^k Y_j \quad k = 1, 2, \dots, n+1$$

then the random variables

$$\left[ \frac{S_1}{S_{n+1}}, \frac{S_2}{S_{n+1}}, \dots, \frac{S_n}{S_{n+1}} \right]$$

given that  $S_{n+1} = s$ , say, have the same distribution as the order statistics from a random sample of size  $n$  from the Uniform distribution on  $(0, 1)$ .

**Proof:** Let the  $Y_j$ s be defined as above. Then the joint density for the  $Y_j$ s is given by

$$\exp \left\{ - \sum_{j=1}^{n+1} y_j \right\} \quad y_1, y_2, \dots, y_{n+1} > 0.$$

Now

$$\left. \begin{array}{l} S_1 = Y_1 \\ S_2 = Y_1 + Y_2 \\ S_3 = Y_1 + Y_2 + Y_3 \\ \vdots \\ S_n = \sum_{j=1}^n Y_j \\ S_{n+1} = \sum_{j=1}^{n+1} Y_j \end{array} \right\} \Leftrightarrow \left\{ \begin{array}{l} Y_1 = S_1 \\ Y_2 = S_2 - S_1 \\ Y_3 = S_3 - S_2 \\ \vdots \\ Y_n = S_n - S_{n-1} \\ Y_{n+1} = S_{n+1} - S_n \end{array} \right.$$

and so the Jacobian of the transformation from  $(Y_1, \dots, Y_{n+1}) \rightarrow (S_1, \dots, S_{n+1})$  is

$$\begin{vmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \vdots & & 1 & 0 \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{vmatrix} = 1$$

and hence the joint density for  $(S_1, \dots, S_{n+1})$  is given by

$$\exp \{-s_{n+1}\} \quad 0 < s_1 < s_2 < \dots < s_{n+1}.$$

The marginal distribution for  $S_{n+1}$  is *Gamma*  $(n+1, 1)$  and thus the conditional distribution of  $(S_1, \dots, S_n)$  given  $S_{n+1} = s$  is

$$\frac{\exp \{-s\}}{\frac{1}{\Gamma(n+1)} s^n \exp \{-s\}} = \frac{n!}{s^n} \quad 0 < s_1 < s_2 < \dots < s.$$

Finally, conditional on  $S_{n+1} = s$ , define the joint transformation

$$V_j = \frac{S_j}{s} \Leftrightarrow S_j = sV_j \quad j = 1, 2, \dots, n$$

which has Jacobian  $s^n$ . Then, conditional on  $S_{n+1} = s$ ,  $(V_1, \dots, V_n)$  have joint pdf equal to  $n!$  for  $0 < v_1 < v_2 < \dots < v_n < 1$ . Finally, if  $U_1, \dots, U_n$  are independent random variables each having a Uniform distribution on  $(0, 1)$ , then  $(U_1, \dots, U_n)$  have joint pdf equal to 1 on the unit hypercube in  $n$  dimensions, and thus the corresponding order statistics  $U_{(1)}, \dots, U_{(n)}$  also have joint pdf equal to

$$n! \quad 0 < u_1 < u_2 < \dots < u_n < 1.$$

**RESULT 2:** Let the  $S_k$  be defined as in Result 1. Then

$$\sqrt{k} \left( \frac{1}{k} S_k - 1 \right) \xrightarrow{\mathcal{L}} N(0, 1) \text{ as } k \rightarrow \infty$$

**Proof:** We have that  $S_k$  is the sum of  $k$  independent and identically distributed *Exponential*(1) random variables,  $Y_1, \dots, Y_k$ , so that  $E[Y_j] = \text{Var}[Y_j] = 1$ . Thus the Central Limit Theorem applies, and the result follows.

**RESULT 3:** Let the  $S_k$  be defined as in Result 1. Then, if

$$\frac{k_1}{n} \rightarrow p_1$$

for some  $p_1$  with  $0 < p_1 < 1$ ,

$$\sqrt{n+1} \left( \frac{1}{n+1} S_{k_1} - \frac{k_1}{n+1} \right) \xrightarrow{\mathcal{L}} N(0, p_1) \text{ as } n \rightarrow \infty$$

**Proof:** We have

$$\sqrt{n+1} \left( \frac{1}{n+1} S_{k_1} - \frac{k_1}{n+1} \right) = \sqrt{\frac{k_1}{n+1}} \sqrt{k_1} \left( \frac{1}{k_1} S_{k_1} - 1 \right) \xrightarrow{\mathcal{L}} \sqrt{p_1} N(0, 1) \equiv N(0, p_1)$$

as  $n \rightarrow \infty$  (so that by assumption  $k_1 \rightarrow \infty$  also).

**Corollary:** Using the same approach, if

$$\frac{k_1}{n} \rightarrow p_1 \quad \text{and} \quad \frac{k_2}{n} \rightarrow p_2$$

for  $0 < p_1 < p_2 < 1$ , then

$$\sqrt{n+1} \left( \frac{1}{n+1} (S_{k_2} - S_{k_1}) - \frac{k_2 - k_1}{n+1} \right) = \sqrt{\frac{k_2 - k_1}{n+1}} \sqrt{k_2 - k_1} \left( \frac{1}{k_2 - k_1} \sum_{j=k_1+1}^{k_2} Y_j - 1 \right)$$

and the right-hand side converges in law to  $\sqrt{p_2 - p_1} N(0, 1) \equiv N(0, p_2 - p_1)$ . Similarly

$$\sqrt{n+1} \left( \frac{1}{n+1} (S_{n+1} - S_{k_2}) - \frac{n+1 - k_2}{n+1} \right) \xrightarrow{\mathcal{L}} N(0, 1 - p_2)$$

where the limiting variables in the three cases are independent, as  $S_{k_1}$ ,  $(S_{k_2} - S_{k_1})$ , and  $(S_{n+1} - S_{k_2})$  are independent.

**RESULT 4:** Let

$$\begin{aligned} Z_1 &= \frac{1}{n+1} S_{k_1} \\ Z_2 &= \frac{1}{n+1} (S_{k_2} - S_{k_1}) \\ Z_3 &= \frac{1}{n+1} (S_{n+1} - S_{k_2}) \end{aligned}$$

and suppose that

$$\sqrt{n} \left( \frac{k_1}{n} - p_1 \right) \rightarrow 0 \text{ and } \sqrt{n} \left( \frac{k_2}{n} - p_2 \right) \rightarrow 0$$

as  $n \rightarrow \infty$ . Then

$$\sqrt{n+1} \left( \begin{pmatrix} Z_1 \\ Z_2 \\ Z_3 \end{pmatrix} - \begin{pmatrix} p_1 \\ p_2 - p_1 \\ 1 - p_2 \end{pmatrix} \right) \xrightarrow{\mathcal{L}} N(0, \Sigma)$$

as  $n \rightarrow \infty$ , where  $\Sigma = \text{diag}(p_1, p_2 - p_1, 1 - p_2)$ .

**Proof:** We have

$$\sqrt{n+1} \left( \frac{1}{n+1} S_{k_1} - p_1 \right) - \sqrt{n+1} \left( \frac{1}{n+1} S_{k_1} - \frac{k_1}{n+1} \right) = \sqrt{n+1} \left( \frac{k_1}{n+1} - p_1 \right) \rightarrow 0$$

as  $n \rightarrow \infty$  by assumption, so

$$\sqrt{n+1} \left( \frac{1}{n+1} S_{k_1} - p_1 \right) \text{ and } \sqrt{n+1} \left( \frac{1}{n+1} S_{k_1} - \frac{k_1}{n+1} \right)$$

have the same asymptotic distribution, and thus the result follows from Result 3. The proof is similar for the other two terms. Independence (that is, the diagonal nature of  $\Sigma$ ) follows from the independence of  $S_{k_1}$ ,  $(S_{k_2} - S_{k_1})$ , and  $(S_{n+1} - S_{k_2})$ .

**RESULT 5:** If  $U_{(1)}, \dots, U_{(n)}$  are the order statistics from a random sample of size  $n$  from a *Uniform*  $(0, 1)$  distribution, and if  $n \rightarrow \infty$ ,  $k_1 \rightarrow \infty$  and  $k_2 \rightarrow \infty$  in such a way that

$$\sqrt{n} \left( \frac{k_1}{n} - p_1 \right) \rightarrow 0 \text{ and } \sqrt{n} \left( \frac{k_2}{n} - p_2 \right) \rightarrow 0$$

for  $0 < p_1 < p_2 < 1$ , then

$$\sqrt{n} \left( \begin{pmatrix} U_{(k_1)} \\ U_{(k_2)} \end{pmatrix} - \begin{pmatrix} p_1 \\ p_2 \end{pmatrix} \right) \xrightarrow{\mathcal{L}} N \left( 0, \begin{bmatrix} p_1(1-p_1) & p_1(1-p_2) \\ p_1(1-p_2) & p_2(1-p_2) \end{bmatrix} \right).$$

**Proof:** Define

$$g(x_1, x_2, x_3) = \frac{1}{x_1 + x_2 + x_3} \begin{bmatrix} x_1 \\ x_1 + x_2 \end{bmatrix}$$

which yields first derivative

$$\dot{g}(x_1, x_2, x_3) = \frac{1}{(x_1 + x_2 + x_3)^2} \begin{bmatrix} x_2 + x_3 & -x_1 & -x_1 \\ x_3 & x_3 & -(x_1 + x_2) \end{bmatrix}.$$

Now

$$g \left( \frac{S_{k_1}}{n+1}, \frac{S_{k_2} - S_{k_1}}{n+1}, \frac{S_{n+1} - S_{k_2}}{n+1} \right) = \frac{1}{S_{n+1}} \begin{bmatrix} S_{k_1} \\ S_{k_2} \end{bmatrix}$$

which has the same distribution as  $(U_{(k_1)}, U_{(k_2)})^T$ , by Result 1. By Cramer's Theorem

$$\sqrt{n} \left( \begin{pmatrix} U_{(k_1)} \\ U_{(k_2)} \end{pmatrix} - \begin{pmatrix} p_1 \\ p_2 \end{pmatrix} \right) \xrightarrow{\mathcal{L}} N \left( 0, \dot{g}(\mu) \Sigma \dot{g}(\mu)^T \right)$$

where  $\Sigma$  is as defined in the Result 4, where here  $\mu = (p_1, p_2 - p_1, 1 - p_2)^T$ . It can be easily verified that

$$\dot{g}(\mu) \Sigma \dot{g}(\mu)^T = \begin{bmatrix} p_1(1-p_1) & p_1(1-p_2) \\ p_1(1-p_2) & p_2(1-p_2) \end{bmatrix}$$

and thus the result follows.

**RESULT 6:** If  $X_{(1)}, \dots, X_{(n)}$  are the order statistics from a random sample of size  $n$  from a distribution with continuous distribution function  $F_X$  and density  $f_X$  which is continuous and non-zero in a neighbourhood of quantiles  $x_{p_1}$  and  $x_{p_2}$  corresponding to probabilities  $p_1 < p_2$ , then if  $k_1 = \lceil np_1 \rceil$  and  $k_2 = \lceil np_2 \rceil$

$$\sqrt{n} \left( \begin{pmatrix} X_{(k_1)} \\ X_{(k_2)} \end{pmatrix} - \begin{pmatrix} x_{p_1} \\ x_{p_2} \end{pmatrix} \right) \xrightarrow{\mathcal{L}} N \left( 0, \begin{bmatrix} \frac{p_1(1-p_1)}{\{f_X(x_{p_1})\}^2} & \frac{p_1(1-p_2)}{f_X(x_{p_1})f_X(x_{p_2})} \\ \frac{p_1(1-p_2)}{f_X(x_{p_1})f_X(x_{p_2})} & \frac{p_2(1-p_2)}{\{f_X(x_{p_2})\}^2} \end{bmatrix} \right)$$

**Proof:** We use the **Delta Method** (Cramer's Theorem) on the result from Result 5, with the transformation

$$g(y_1, y_2) = \begin{bmatrix} F_X^{-1}(y_1) \\ F_X^{-1}(y_2) \end{bmatrix}$$

so that

$$\dot{g}(y_1, y_2) = \begin{bmatrix} \frac{1}{f_X(F_X^{-1}(y_1))} & 0 \\ 0 & \frac{1}{f_X(F_X^{-1}(y_2))} \end{bmatrix}$$

with  $y_1 = p_1$  and  $y_2 = p_2$ .