

## 9 Appendix C

Appendix C is devoted to deriving a closed-form expression for the information matrix and to verifying the information matrix equality. Proofs of Lemmas 4 and 5 are also provided.

*Proof of Lemma 4.* From (31), taking  $k = 2$ , we get  $\Psi'(x) = \sum_{i=0}^{\infty} 1/(x+i)^2 > 0$  for all  $x$ , implying that  $\Psi(v)$  is a strictly increasing function. From the above expression for  $\Psi'(x)$ , we can also see that  $\Psi'(x)$  is a strictly decreasing function for  $x > 0$ , implying  $D'(v) = \Psi'(\frac{v+1}{2}) - \Psi'(\frac{v}{2}) < 0$ . So  $D(v)$  is strictly decreasing. If the first equality in (32) holds, then the second one is easily verified. Now we proceed to show the first equality. In fact, differentiating both sides of  $\Gamma(x+1) = x\Gamma(x)$  leads to  $\Gamma'(x+1)/\Gamma(x) = 1+x\Psi(x)$ , and then rewriting it does yield the first equality in (32). ■

*Proof of Lemma 5.* The proofs are immediate. For equality (33), taking the log of the expression for  $K(v)$  and then differentiating both sides, it follows that

$$\begin{aligned} \frac{K'(v)}{K(v)} &= \frac{d \ln K(v)}{dv} = d \left[ \ln \Gamma((v+1)/2) - \ln \Gamma(v/2) - \frac{1}{2} \ln v - \ln \sqrt{\pi} \right] / dv \\ &= \frac{1}{2} \left[ \Psi\left(\frac{v+1}{2}\right) - \Psi\left(\frac{v}{2}\right) - \frac{1}{v} \right]. \end{aligned}$$

So we have shown that (33) holds. From the definition of  $K(v)$ , the left side of equality (34) is expressed as

$$\left( \frac{v}{v+2j} \right)^{1/2} \frac{K(v)}{K(v+2j)} = \frac{\Gamma((v+1)/2)}{\Gamma(v/2)} \frac{\Gamma(v/2+j)}{\Gamma((v+1)/2+j)}.$$

Using the fact  $\Gamma(v+1) = v\Gamma(v)$ , the proof of equality (34) is easily completed. ■

Now suppose that  $y_t$  ( $t = 1, 2, \dots, T$ ) are i.i.d. observations from the AST with density  $f(y; \theta_0)$  defined in (5), where  $\theta_0 = (\alpha_0, v_{01}, v_{02}, \mu_0, \sigma_0)$ . Expectations are always taken with respect to the true underlying distribution  $f(y; \theta_0)$ . Then the log-density function with parameter  $\theta$  is  $\ln f(y_t; \theta) =$

$$-\ln \sigma - \frac{v_1 + 1}{2} [\ln L(y_t; \theta)] 1(y_t < \mu) - \frac{v_2 + 1}{2} [\ln R(y_t; \theta)] 1(y_t > \mu)$$

and the score vector for observation  $t$ ,  $\frac{\partial}{\partial \theta} \ln f(y_t; \theta)$ , is given by

$$\begin{aligned} \frac{\partial \ln f}{\partial \alpha} &= \frac{v_1 + 1}{\alpha} \left[ 1 - \frac{1}{L(y_t; \theta)} \right] 1(y_t < \mu) \\ &\quad - \frac{v_2 + 1}{1 - \alpha} \left[ 1 - \frac{1}{R(y_t; \theta)} \right] 1(y_t > \mu), \end{aligned} \quad (56)$$

$$\frac{\partial \ln f}{\partial v_1} = \left\{ -\frac{1}{2} \ln L(y_t; \theta) + \frac{v_1 + 1}{2} D(v_1) \frac{L(y_t; \theta) - 1}{L(y_t; \theta)} \right\} 1(y_t < \mu), \quad (57)$$

$$\frac{\partial \ln f}{\partial v_2} = \left\{ -\frac{1}{2} \ln R(y_t; \theta) + \frac{v_2 + 1}{2} D(v_2) \frac{R(y_t; \theta) - 1}{R(y_t; \theta)} \right\} 1(y_t > \mu), \quad (58)$$

$$\begin{aligned} \frac{\partial \ln f}{\partial \mu} &= \frac{v_1 + 1}{2} \frac{1}{L(y_t; \theta)} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \\ &\quad + \frac{v_2 + 1}{2} \frac{1}{R(y_t; \theta)} \frac{1}{v_2} \frac{2(y_t - \mu)}{[2(1 - \alpha)\sigma K(v_2)]^2} 1(y_t > \mu), \end{aligned} \quad (59)$$

$$\begin{aligned} \frac{\partial \ln f}{\partial \sigma} &= -\frac{1}{\sigma} + \frac{v_1 + 1}{\sigma} \left[ 1 - \frac{1}{L(y_t; \theta)} \right] 1(y_t < \mu) \\ &\quad + \frac{v_2 + 1}{\sigma} \left[ 1 - \frac{1}{R(y_t; \theta)} \right] 1(y_t > \mu), \end{aligned} \quad (60)$$

where we used equality (33) in the expressions for the components  $\frac{\partial \ln f}{\partial v_1}$  and  $\frac{\partial \ln f}{\partial v_2}$ . To derive the information matrix  $I(\theta_0) \equiv E[\frac{\partial}{\partial \theta} \ln f(y_t; \theta_0) \frac{\partial}{\partial \theta'} \ln f(y_t; \theta_0)]$  and the Hessian  $H(\theta_0) \equiv E[\frac{\partial^2}{\partial \theta \partial \theta'} \ln f(y_t; \theta_0)]$  and to verify the information matrix equality  $I(\theta_0) = -H(\theta_0)$ , the following Lemma is needed.

**Lemma 9** *For any  $j, m = 0, 1, 2, \dots$ , the following moment equalities hold:*

$$\begin{aligned} E \left\{ \frac{1}{[L(y_t; \theta_0)]^j} 1(y_t < \mu_0) \right\} &= \alpha \left( \frac{v_1}{v_1 + 2j} \right)^{1/2} \frac{K(v_1)}{K(v_1 + 2j)} \quad (61) \\ &= \begin{cases} \alpha, & j = 0, \\ \alpha v_1 / (v_1 + 1), & j = 1, \\ \alpha \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)}, & j = 2; \end{cases} \end{aligned}$$

$$\begin{aligned} E \left\{ \frac{1}{[R(y_t; \theta_0)]^j} 1(y_t > \mu_0) \right\} &= (1 - \alpha) \left( \frac{v_2}{v_2 + 2j} \right)^{1/2} \frac{K(v_2)}{K(v_2 + 2j)} \quad (62) \\ &= \begin{cases} (1 - \alpha), & j = 0, \\ (1 - \alpha) v_2 / (v_2 + 1), & j = 1, \\ (1 - \alpha) \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)}, & j = 2; \end{cases} \end{aligned}$$

$$\begin{aligned}
E \left\{ \frac{\ln L(y_t; \theta_0)}{[L(y_t; \theta_0)]^j} 1(y_t < \mu_0) \right\} &= \alpha \left( \frac{v_1}{v_1 + 2j} \right)^{1/2} \frac{K(v_1)}{K(v_1 + 2j)} D(v_1 + 2j) \\
&= \begin{cases} \alpha D(v_1), & j = 0, \\ \alpha \left( \frac{v_1}{v_1 + 1} \right) D(v_1 + 2), & j = 1; \end{cases} \quad (63)
\end{aligned}$$

$$\begin{aligned}
E \left\{ \frac{\ln R(y_t; \theta_0)}{[R(y_t; \theta_0)]^j} 1(y_t > \mu_0) \right\} &= (1 - \alpha) \left( \frac{v_2}{v_2 + 2j} \right)^{1/2} \frac{K(v_2) D(v_2 + 2j)}{K(v_2 + 2j)} \\
&= \begin{cases} (1 - \alpha) D(v_2), & j = 0, \\ (1 - \alpha) \left( \frac{v_2}{v_2 + 1} \right) D(v_2 + 2), & j = 1; \end{cases} \quad (64)
\end{aligned}$$

$$E \left\{ \frac{(y_t - \mu_0) [\ln L(y_t; \theta_0)]^m}{[L(y_t; \theta_0)]^j} 1(y_t < \mu_0) \right\} = -\frac{2^{m+1} m! v_1 [2\alpha \sigma K(v_1)]^2}{2\sigma (v_1 + 2j - 1)^{m+1}}, \quad (65)$$

$$E \left\{ \frac{(y_t - \mu_0) [\ln R(y_t; \theta_0)]^m}{[R(y_t; \theta_0)]^j} 1(y_t > \mu_0) \right\} = \frac{2^{m+1} m! v_2 [2(1 - \alpha) \sigma K(v_2)]^2}{2\sigma (v_2 + 2j - 1)^{m+1}}, \quad (66)$$

$$E \left\{ [\ln L(y_t; \theta_0)]^2 1(y_t < \mu_0) \right\} = \alpha [D^2(v_1) - 2D'(v_1)], \quad (67)$$

$$E \left\{ [\ln R(y_t; \theta_0)]^2 1(y_t > \mu_0) \right\} = (1 - \alpha) [D^2(v_2) - 2D'(v_2)], \quad (68)$$

where the right hand sides of all the equalities from (61) to (68) are evaluated at the true values  $(\alpha_0, v_{01}, v_{02}, \mu_0, \sigma_0)$ .

*Proof.*<sup>4</sup> We discuss equalities (61), (63), (65) and (67). Other equalities can be proved in the same manner. Note that, for any  $j, m = 0, 1, 2, \dots$ ,

$$\begin{aligned}
EL_1(j, m) &\equiv E \left\{ [L(y_t; \theta)]^{-j} [\ln L(y_t; \theta)]^m 1(y_t < \mu) \right\} \\
&= \int_{-\infty}^{\mu} [L(y; \theta)]^{-j} [\ln L(y; \theta)]^m \frac{1}{\sigma} [L(y; \theta)]^{-(v_1+1)/2} dy,
\end{aligned}$$

and that  $L(y; \theta) \equiv 1 + \frac{y - \mu}{v_1 \left( \frac{y - \mu}{2\alpha\sigma K(v_1)} \right)^2}$ . Then using the change of variable  $z = -\frac{y - \mu}{2\alpha\sigma\sqrt{v_1}K(v_1)}$  yields

$$EL_1(j, m) = 2\alpha\sqrt{v_1}K(v_1) \int_0^{+\infty} (1 + z^2)^{-(v_1+2j+1)/2} [\ln(1 + z^2)]^m dz. \quad (69)$$

Setting  $m = 0$ ,  $m = 1$ , and  $(j, m) = (0, 2)$  respectively, and correspondingly taking into account equality (35) with  $v = v_1 + 2j$ , equality (36) with  $v =$

<sup>4</sup>For simplicity, we omit the subscript on the true parameters  $\theta_0$  in all the following proofs.

$v_1 + 2j$ , and equality (37) with  $v = v_1$ , we obtain equalities (61), (63), and (67). These proofs use (34). Now consider equality (65). Denote by  $EL_2(j, m)$  the expectation of the left side of equality (65), and note that the change of variable  $z = \frac{1}{v_1} \left( \frac{y - \mu}{2\alpha\sigma K(v_1)} \right)^2$  yields

$$EL_2(j, m) = -\frac{v_1 [2\alpha\sigma K(v_1)]^2}{2\sigma} \int_0^{+\infty} (1+z)^{-(v_1+2j+1)/2} [\ln(1+z)]^m dz. \quad (70)$$

Subject to  $v_1 + 2j - 1 > 0$ , by integration by parts it follows that

$$EL_2(j, m) = m \left( \frac{2}{v_1 + 2j - 1} \right) EL_2(j, m-1) = m! \left( \frac{2}{v_1 + 2j - 1} \right)^m EL_2(j, 0).$$

A straightforward calculation for (70) gives  $EL_2(j, 0) = -\frac{v_1 [2\alpha\sigma K(v_1)]^2}{\sigma(v_1+2j-1)}$ . ■

**Lemma 10** *The score vector for observation  $t$ ,  $\frac{\partial}{\partial \theta} \ln f(y_t; \theta)$ , satisfies the equation*

$$E \left[ \frac{\partial}{\partial \theta} \ln f(y_t; \theta_0) \right] = 0. \quad (71)$$

*Proof.* By using the equalities from (61) to (68), this Lemma is easily verified. In fact,

(i).

$$\begin{aligned} E \left[ \frac{\partial \ln f}{\partial \alpha} \right] &= \frac{v_1 + 1}{\alpha} E \left\{ \left[ 1 - \frac{1}{L(y_t; \theta)} \right] 1(y_t < \mu) \right\} \\ &\quad - \frac{v_2 + 1}{1 - \alpha} E \left\{ \left[ 1 - \frac{1}{R(y_t; \theta)} \right] 1(y_t > \mu) \right\} \\ &= \frac{v_1 + 1}{\alpha} \alpha \left( 1 - \frac{v_1}{v_1 + 1} \right) - \frac{v_2 + 1}{1 - \alpha} (1 - \alpha) \left( 1 - \frac{v_2}{v_2 + 1} \right) = 0. \end{aligned}$$

(ii).

$$\begin{aligned} E \left[ \frac{\partial \ln f}{\partial v_1} \right] &= E \left\{ \left[ -\frac{\ln L(y_t; \theta)}{2} + \frac{v_1 + 1}{2} D(v_1) \frac{L(y_t; \theta) - 1}{L(y_t; \theta)} \right] 1(y_t < \mu) \right\} \\ &= -\frac{1}{2} \alpha D(v_1) + \frac{v_1 + 1}{2} D(v_1) \alpha \left( 1 - \frac{v_1}{v_1 + 1} \right) = 0. \end{aligned}$$

(iii). Similarly, we have

$$E \left[ \frac{\partial \ln f}{\partial v_2} \right] = E \left\{ \left[ \frac{v_2 + 1}{2} D(v_2) \frac{R(y_t; \theta) - 1}{R(y_t; \theta)} - \frac{\ln R(y_t; \theta)}{2} \right] 1(y_t > \mu) \right\} = 0.$$

(iv).

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial \mu} \right] &= \frac{v_1 + 1}{2} E \left\{ \frac{1}{L(y_t; \theta)} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&\quad + \frac{v_2 + 1}{2} E \left\{ \frac{1}{R(y_t; \theta)} \frac{1}{v_2} \frac{2(y_t - \mu)}{[2(1 - \alpha)\sigma K(v_2)]^2} 1(y_t > \mu) \right\} \\
&= \frac{v_1 + 1}{2} \frac{-2}{\sigma(v_1 + 1)} + \frac{v_2 + 1}{2} \frac{2}{\sigma(v_2 + 1)} = 0.
\end{aligned}$$

(v).

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial \sigma} \right] &= -\frac{1}{\sigma} + \frac{v_1 + 1}{\sigma} E \left\{ \left[ 1 - \frac{1}{L(y_t; \theta)} \right] 1(y_t < \mu) \right\} \\
&\quad + \frac{v_2 + 1}{\sigma} E \left\{ \left[ 1 - \frac{1}{R(y_t; \theta)} \right] 1(y_t > \mu) \right\} \\
&= -\frac{1}{\sigma} + \frac{v_1 + 1}{\sigma} \alpha \left( 1 - \frac{v_1}{v_1 + 1} \right) + \frac{v_2 + 1}{\sigma} \frac{(1 - \alpha)}{v_2 + 1} \\
&= -\frac{1}{\sigma} + \frac{\alpha}{\sigma} + \frac{1 - \alpha}{\sigma} = 0. \blacksquare
\end{aligned}$$

*Proof of Proposition 2.* We prove this by computing expectations on the both sides of the following equations and then verifying them,

$$E \left[ \frac{\partial \ln f(y_t; \theta)}{\partial \theta_i} \cdot \frac{\partial \ln f(y_t; \theta)}{\partial \theta_j} \right] = -E \left[ \frac{\partial^2 \ln f(y_t; \theta)}{\partial \theta_i \partial \theta_j} \right], \quad i, j = 1, 2, \dots, 5.$$

In the proof, the fact that  $1(y_t < \mu)1(y_t > \mu) = 0$  and the equalities (61)-(68) are used repeatedly. In addition, we use  $E[\frac{\partial}{\partial \theta} \ln f(y_t; \theta_0)] = 0$  shown in (71) and  $D(v + 2) = -\frac{2}{v(v+1)} + D(v)$  given in (32). Note that by the construction of the AST distribution, the left-tail parameter  $v_1$  and the right-tail parameter  $v_2$  have a symmetry property. Hence we do not consider the terms of the information matrix equality involved in the right-tail parameter  $v_2$ .

(a)

$$\begin{aligned} E \left[ \frac{\partial \ln f}{\partial \alpha} \right]^2 &= \left( \frac{v_1 + 1}{\alpha} \right)^2 E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right)^2 1(y_t < \mu) \right\} \\ &\quad + \left( \frac{v_2 + 1}{1 - \alpha} \right)^2 E \left\{ \left( 1 - \frac{1}{R(y_t; \theta)} \right)^2 1(y_t > \mu) \right\} \\ &= \left( \frac{v_1 + 1}{\alpha} \right)^2 \alpha \left[ 1 - 2 \frac{v_1}{v_1 + 1} + \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\ &\quad + \left( \frac{v_2 + 1}{1 - \alpha} \right)^2 (1 - \alpha) \left[ 1 - \frac{2v_2}{v_2 + 1} + \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\ &= 3 \left[ \frac{v_1 + 1}{\alpha(v_1 + 3)} + \frac{v_2 + 1}{(1 - \alpha)(v_2 + 3)} \right]; \end{aligned}$$

$$\begin{aligned} E \left[ \frac{\partial^2 \ln f}{\partial \alpha^2} \right] &= -\frac{v_1 + 1}{\alpha^2} E \left\{ \left[ 1 + \frac{1}{L(y_t; \theta)} - \frac{2}{[L(y_t; \theta)]^2} \right] 1(y_t < \mu) \right\} \\ &\quad - \frac{v_2 + 1}{(1 - \alpha)^2} E \left\{ \left[ 1 + \frac{1}{R(y_t; \theta)} - \frac{2}{[R(y_t; \theta)]^2} \right] 1(y_t > \mu) \right\} \\ &= -\frac{v_1 + 1}{\alpha^2} \alpha \left[ 1 + \frac{v_1}{v_1 + 1} - 2 \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\ &\quad - \frac{v_2 + 1}{(1 - \alpha)^2} (1 - \alpha) \left[ 1 + \frac{v_2}{v_2 + 1} - 2 \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\ &= -3 \left[ \frac{v_1 + 1}{\alpha(v_1 + 3)} + \frac{v_2 + 1}{(1 - \alpha)(v_2 + 3)} \right]. \end{aligned}$$

(b)

$$\begin{aligned}
& E \left[ \frac{\partial \ln f}{\partial v_1} \right]^2 \\
= & E \left\{ \left[ \frac{[\ln L(y_t; \theta)]^2}{4} + \left( \frac{v_1 + 1}{2} \right)^2 D^2(v_1) \left( 1 - \frac{1}{L(y_t; \theta)} \right)^2 \right] 1(y_t < \mu) \right\} \\
& - \left( \frac{v_1 + 1}{2} \right) D(v_1) E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right) \ln L(y_t; \theta) 1(y_t < \mu) \right\} \\
= & \alpha \frac{D^2(v_1) - 2D'(v_1)}{4} + \left( \frac{v_1 + 1}{2} \right)^2 D^2(v_1) \frac{3\alpha}{(v_1 + 1)(v_1 + 3)} \\
& - \left( \frac{v_1 + 1}{2} \right) D(v_1) \alpha \left[ D(v_1) - \frac{v_1}{v_1 + 1} D(v_1 + 2) \right] \\
= & \frac{\alpha}{2} \left\{ \frac{v_1}{v_1 + 3} D^2(v_1) - \frac{2}{v_1 + 1} D(v_1) - D'(v_1) \right\};
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial v_1^2} \right] &= \left[ D(v_1) + \frac{v_1 + 1}{2} D'(v_1) \right] E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right) 1(y_t < \mu) \right\} \\
&\quad - \frac{v_1 + 1}{2} D^2(v_1) E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{1}{[L(y_t; \theta)]^2} \right) 1(y_t < \mu) \right\} \\
&= \left[ D(v_1) + \frac{v_1 + 1}{2} D'(v_1) \right] \alpha \left[ 1 - \frac{v_1}{v_1 + 1} \right] \\
&\quad - \frac{v_1 + 1}{2} D^2(v_1) \alpha \left[ \frac{v_1}{v_1 + 1} - \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&= -\frac{\alpha}{2} \left\{ \frac{v_1}{v_1 + 3} D^2(v_1) - \frac{2}{v_1 + 1} D(v_1) - D'(v_1) \right\}.
\end{aligned}$$

(c).

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial \mu} \right]^2 &= \frac{1}{v_1} \left[ \frac{v_1 + 1}{2\alpha\sigma K(v_1)} \right]^2 E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{1}{[L(y_t; \theta)]^2} \right) 1(y_t < \mu) \right\} \\
&\quad + \frac{1}{v_2} \left[ \frac{v_2 + 1}{2(1-\alpha)\sigma K(v_2)} \right]^2 E \left\{ \left( \frac{1(y_t > \mu)}{R(y_t; \theta)} - \frac{1(y_t > \mu)}{[R(y_t; \theta)]^2} \right) \right\} \\
&= \left[ \frac{v_1 + 1}{2\alpha\sigma K(v_1)} \right]^2 \frac{\alpha}{v_1} \left[ \frac{v_1}{v_1 + 1} - \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] + \\
&\quad + \left[ \frac{v_2 + 1}{2(1-\alpha)\sigma K(v_2)} \right]^2 \frac{1-\alpha}{v_2} \left[ \frac{v_2}{v_2 + 1} - \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\
&= \frac{1}{4\sigma^2} \left[ \frac{v_1 + 1}{\alpha(v_1 + 3)} \frac{1}{K^2(v_1)} + \frac{v_2 + 1}{(1-\alpha)(v_2 + 3)} \frac{1}{K^2(v_2)} \right].
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial \mu^2} \right] &= \frac{1}{v_1} \frac{v_1 + 1}{[2\alpha\sigma K(v_1)]^2} E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{2}{[L(y_t; \theta)]^2} \right) 1(y_t < \mu) \right\} \\
&\quad + \frac{1}{v_2} \frac{v_2 + 1}{[2(1-\alpha)\sigma K(v_2)]^2} E \left\{ \frac{1(y_t > \mu)}{R(y_t; \theta)} - 2 \frac{1(y_t > \mu)}{[R(y_t; \theta)]^2} \right\} \\
&= \frac{v_1 + 1}{[2\alpha\sigma K(v_1)]^2} \frac{\alpha}{v_1} \left[ \frac{v_1}{v_1 + 1} - \frac{2v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&\quad + \frac{v_2 + 1}{[2(1-\alpha)\sigma K(v_2)]^2} \frac{1-\alpha}{v_2} \left[ \frac{v_2}{v_2 + 1} - \frac{2v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\
&= -\frac{1}{4\sigma^2} \left[ \frac{v_1 + 1}{\alpha(v_1 + 3)} \frac{1}{K^2(v_1)} + \frac{v_2 + 1}{(1-\alpha)(v_2 + 3)} \frac{1}{K^2(v_2)} \right].
\end{aligned}$$

(d).

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial \sigma} \right]^2 &= 0 - \frac{1}{\sigma^2} + \left( \frac{v_1 + 1}{\sigma} \right)^2 E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right)^2 1(y_t < \mu) \right\} \\
&\quad + \left( \frac{v_2 + 1}{\sigma} \right)^2 E \left\{ \left( 1 - \frac{1}{R(y_t; \theta)} \right)^2 1(y_t > \mu) \right\} \\
&= -\frac{1}{\sigma^2} + \left( \frac{v_1 + 1}{\sigma} \right)^2 \alpha \left[ 1 - 2 \frac{v_1}{v_1 + 1} + \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&\quad + \left( \frac{v_2 + 1}{\sigma} \right)^2 (1-\alpha) \left[ 1 - 2 \frac{v_2}{v_2 + 1} + \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\
&= \frac{2}{\sigma^2} \left[ \alpha \frac{v_1}{v_1 + 3} + (1-\alpha) \frac{v_2}{v_2 + 3} \right];
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial \sigma^2} \right] &= \frac{1}{\sigma^2} - \frac{v_1 + 1}{\sigma^2} E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right) \left( 1 + \frac{2}{L(y_t; \theta)} \right) 1(y_t < \mu) \right\} \\
&\quad - \frac{v_2 + 1}{\sigma^2} E \left\{ \left( 1 - \frac{1}{R(y_t; \theta)} \right) \left( 1 + \frac{2}{R(y_t; \theta)} \right) 1(y_t > \mu) \right\} \\
&= \frac{1}{\sigma^2} - \frac{v_1 + 1}{\sigma^2} \alpha \left[ 1 + \frac{v_1}{v_1 + 1} - 2 \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&\quad - \frac{v_2 + 1}{\sigma^2} (1 - \alpha) \left[ 1 + \frac{v_2}{v_2 + 1} - 2 \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\
&= -\frac{2}{\sigma^2} \left[ \alpha \frac{v_1}{v_1 + 3} + (1 - \alpha) \frac{v_2}{v_2 + 3} \right].
\end{aligned}$$

(e).

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial \alpha} \frac{\partial \ln f}{\partial v_1} \right] &= -\frac{v_1 + 1}{2\alpha} E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right) \ln L(y_t; \theta) 1(y_t < \mu) \right\} \\
&\quad + \frac{(v_1 + 1)^2}{2\alpha} D(v_1) E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right)^2 1(y_t < \mu) \right\} \\
&= -\frac{v_1 + 1}{2\alpha} \alpha \left[ D(v_1) - \frac{v_1}{v_1 + 1} D(v_1 + 2) \right] \\
&\quad + \frac{(v_1 + 1)^2}{2\alpha} D(v_1) \alpha \left[ 1 - \frac{2v_1}{v_1 + 1} + \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&= -\frac{1}{v_1 + 1} + \frac{v_1}{v_1 + 3} D(v_1);
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial \alpha \partial v_1} \right] &= \frac{1}{\alpha} E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right) 1(y_t < \mu) \right\} \\
&\quad - \frac{v_1 + 1}{\alpha} D(v_1) E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{1}{[L(y_t; \theta)]^2} \right) 1(y_t < \mu) \right\} \\
&= \frac{1}{\alpha} \alpha \left[ 1 - \frac{v_1}{v_1 + 1} \right] - \frac{v_1 + 1}{\alpha} D(v_1) \frac{\alpha v_1}{v_1 + 1} \left[ 1 - \frac{v_1 + 2}{v_1 + 3} \right] \\
&= \frac{1}{v_1 + 1} - \frac{v_1}{v_1 + 3} D(v_1).
\end{aligned}$$

(f).

$$\begin{aligned}
& E \left[ \frac{\partial \ln f}{\partial \alpha} \frac{\partial \ln f}{\partial \mu} \right] \\
&= \frac{(v_1 + 1)^2}{2\alpha} E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{1}{[L(y_t; \theta)]^2} \right) \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&\quad - \frac{(v_2 + 1)^2}{2(1 - \alpha)} E \left\{ \left( \frac{1}{R(y_t; \theta)} - \frac{1}{[R(y_t; \theta)]^2} \right) \frac{1}{v_2} \frac{2(y_t - \mu)1(y_t > \mu)}{[2(1 - \alpha)\sigma K(v_2)]^2} \right\} \\
&= \frac{(v_1 + 1)^2}{2\alpha\sigma} \left[ -\frac{2}{v_1 + 1} + \frac{2}{v_1 + 3} \right] - \frac{(v_2 + 1)^2}{2(1 - \alpha)\sigma} \left[ \frac{2}{v_2 + 1} - \frac{2}{v_2 + 3} \right] \\
&= -\frac{2}{\sigma} \left[ \frac{v_1 + 1}{\alpha(v_1 + 3)} + \frac{v_2 + 1}{(1 - \alpha)(v_2 + 3)} \right];
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial \alpha \partial \mu} \right] &= -\frac{v_1 + 1}{\alpha} E \left\{ \frac{1}{[L(y_t; \theta)]^2} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&\quad + \frac{v_2 + 1}{1 - \alpha} E \left\{ \frac{1}{[R(y_t; \theta)]^2} \frac{1}{v_2} \frac{2(y_t - \mu)}{[2(1 - \alpha)\sigma K(v_2)]^2} 1(y_t > \mu) \right\} \\
&= \frac{v_1 + 1}{\alpha} \frac{1}{\sigma} \frac{2}{v_1 + 3} + \frac{v_2 + 1}{1 - \alpha} \frac{1}{\sigma} \frac{2}{v_2 + 3} \\
&= \frac{2}{\sigma} \left[ \frac{v_1 + 1}{\alpha(v_1 + 3)} + \frac{v_2 + 1}{(1 - \alpha)(v_2 + 3)} \right].
\end{aligned}$$

(g).

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial \alpha} \frac{\partial \ln f}{\partial \sigma} \right] &= -\frac{1}{\sigma} E \left[ \frac{\partial \ln f}{\partial \alpha} \right] + \frac{(v_1 + 1)^2}{\alpha\sigma} E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right)^2 1(y_t < \mu) \right\} \\
&\quad - \frac{(v_2 + 1)^2}{(1 - \alpha)\sigma} E \left\{ \left( 1 - \frac{1}{R(y_t; \theta)} \right)^2 1(y_t > \mu) \right\} \\
&= 0 + \frac{(v_1 + 1)^2}{\alpha\sigma} \alpha \left[ 1 - \frac{2v_1}{v_1 + 1} + \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&\quad - \frac{(v_2 + 1)^2}{(1 - \alpha)\sigma} (1 - \alpha) \left[ 1 - \frac{2v_2}{v_2 + 1} + \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\
&= \frac{2}{\sigma} \left[ \frac{v_1}{v_1 + 3} - \frac{v_2}{v_2 + 3} \right];
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial \alpha \partial \sigma} \right] &= -2 \left( \frac{v_1 + 1}{\alpha \sigma} \right) E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{1}{[L(y_t; \theta)]^2} \right) 1(y_t < \mu) \right\} \\
&\quad + 2 \left[ \frac{v_2 + 1}{(1 - \alpha) \sigma} \right] E \left\{ \left( \frac{1}{R(y_t; \theta)} - \frac{1}{[R(y_t; \theta)]^2} \right) 1(y_t > \mu) \right\} \\
&= -2 \left( \frac{v_1 + 1}{\alpha \sigma} \right) \alpha \left[ \frac{v_1}{v_1 + 1} - \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&\quad + 2 \left( \frac{v_2 + 1}{(1 - \alpha) \sigma} \right) (1 - \alpha) \left[ \frac{v_2}{v_2 + 1} - \frac{v_2(v_2 + 2)}{(v_2 + 1)(v_2 + 3)} \right] \\
&= -\frac{2}{\sigma} \left( \frac{v_1}{v_1 + 3} - \frac{v_2}{v_2 + 3} \right).
\end{aligned}$$

(h). Note that  $\frac{\partial \ln f}{\partial v_1} \frac{\partial \ln f}{\partial v_2} = 0$  and  $\frac{\partial^2 \ln f}{\partial v_1 \partial v_2} = 0$ . Then we have

$$E \left( \frac{\partial \ln f}{\partial v_1} \frac{\partial \ln f}{\partial v_2} \right) = -E \left( \frac{\partial^2 \ln f}{\partial v_1 \partial v_2} \right) = 0.$$

(i).

$$\begin{aligned}
&E \left[ \frac{\partial \ln f}{\partial v_1} \frac{\partial \ln f}{\partial \mu} \right] \\
&= -\frac{v_1 + 1}{4} E \left\{ \frac{1}{L(y_t; \theta)} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} \ln L(y_t; \theta) 1(y_t < \mu) \right\} \\
&\quad + \left( \frac{v_1 + 1}{2} \right)^2 D(v_1) E \left\{ \frac{1}{L(y_t; \theta)} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&\quad - \left( \frac{v_1 + 1}{2} \right)^2 D(v_1) E \left\{ \frac{1}{[L(y_t; \theta)]^2} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&= \frac{v_1 + 1}{4\sigma} \left( \frac{2}{v_1 + 1} \right)^2 - \left( \frac{v_1 + 1}{2} \right)^2 \frac{D(v_1)}{\sigma} \left[ \frac{2}{v_2 + 1} - \frac{2}{v_2 + 3} \right] \\
&= \frac{1}{\sigma} \left[ \frac{1}{v_1 + 1} - \frac{v_1 + 1}{v_1 + 3} D(v_1) \right]; \\
E \left[ \frac{\partial^2 \ln f}{\partial v_1 \partial \mu} \right] &= \frac{1}{2} E \left\{ \frac{1}{L(y_t; \theta)} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&\quad - \left( \frac{v_1 + 1}{2} \right) D(v_1) E \left\{ \frac{1}{[L(y_t; \theta)]^2} \frac{1}{v_1} \frac{2(y_t - \mu) 1(y_t < \mu)}{[2\alpha\sigma K(v_1)]^2} \right\} \\
&= -\frac{1}{2} \frac{1}{\sigma} \left( \frac{2}{v_1 + 1} \right) + \left( \frac{v_1 + 1}{2} \right) D(v_1) \frac{1}{\sigma} \frac{2}{v_2 + 3} \\
&= -\frac{1}{\sigma} \left[ \frac{1}{v_1 + 1} - \frac{v_1 + 1}{v_1 + 3} D(v_1) \right].
\end{aligned}$$

(j).

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial v_1} \frac{\partial \ln f}{\partial \sigma} \right] &= 0 - \frac{v_1 + 1}{2\sigma} E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right) \ln L(y_t; \theta) 1(y_t < \mu) \right\} \\
&\quad + \frac{(v_1 + 1)^2}{2\sigma} D(v_1) E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right)^2 1(y_t < \mu) \right\} \\
&= -\frac{v_1 + 1}{2\sigma} \alpha \left[ D(v_1) - \frac{v_1}{v_1 + 1} D(v_1 + 2) \right] \\
&\quad + \frac{(v_1 + 1)^2}{2\sigma} D(v_1) \alpha \left[ 1 - 2 \frac{v_1}{v_1 + 1} + \frac{v_1(v_1 + 2)}{(v_1 + 1)(v_1 + 3)} \right] \\
&= \frac{\alpha}{\sigma} \left[ -\frac{1}{v_1 + 1} + \frac{v_1}{v_1 + 3} D(v_1) \right];
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial v_1 \partial \sigma} \right] &= \frac{1}{\sigma} E \left\{ \left( 1 - \frac{1}{L(y_t; \theta)} \right) 1(y_t < \mu) \right\} \\
&\quad - \frac{v_1 + 1}{\sigma} D(v_1) E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{1}{[L(y_t; \theta)]^2} \right) 1(y_t < \mu) \right\} \\
&= \frac{1}{\sigma} \alpha \left[ 1 - \frac{v_1}{v_1 + 1} \right] - \frac{v_1 + 1}{\sigma} D(v_1) \alpha \frac{v_1}{v_1 + 1} \left[ 1 - \frac{v_1 + 2}{v_1 + 3} \right] \\
&= \frac{\alpha}{\sigma} \left[ \frac{1}{v_1 + 1} - \frac{v_1}{v_1 + 3} D(v_1) \right].
\end{aligned}$$

(k).

$$\begin{aligned}
&E \left[ \frac{\partial \ln f}{\partial \mu} \frac{\partial \ln f}{\partial \sigma} \right] \\
&= \frac{(v_1 + 1)^2}{2\sigma} E \left\{ \left( \frac{1}{L(y_t; \theta)} - \frac{1}{[L(y_t; \theta)]^2} \right) \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&\quad + \frac{(v_2 + 1)^2}{2\sigma} E \left\{ \left( \frac{1}{R(y_t; \theta)} - \frac{1}{[R(y_t; \theta)]^2} \right) \frac{1}{v_2} \frac{2(y_t - \mu) 1(y_t > \mu)}{[2(1 - \alpha)\sigma K(v_1)]^2} \right\} \\
&= \frac{(v_1 + 1)^2}{2\sigma^2} \left[ -\frac{2}{v_1 + 1} + \frac{2}{v_1 + 3} \right] + \frac{(v_2 + 1)^2}{2\sigma^2} \left[ \frac{2}{v_2 + 1} - \frac{2}{v_2 + 3} \right] \\
&= \frac{2}{\sigma^2} \left[ -\frac{v_1 + 1}{v_1 + 3} + \frac{v_2 + 1}{v_2 + 3} \right];
\end{aligned}$$

$$\begin{aligned}
E \left[ \frac{\partial^2 \ln f}{\partial \mu \partial \sigma} \right] &= -\frac{v_1 + 1}{\sigma} E \left\{ \frac{1}{[L(y_t; \theta)]^2} \frac{1}{v_1} \frac{2(y_t - \mu)}{[2\alpha\sigma K(v_1)]^2} 1(y_t < \mu) \right\} \\
&\quad - \frac{v_2 + 1}{\sigma} E \left\{ \frac{1}{[R(y_t; \theta)]^2} \frac{1}{v_2} \frac{2(y_t - \mu)}{[2(1 - \alpha)\sigma K(v_1)]^2} 1(y_t > \mu) \right\} \\
&= \left( \frac{v_1 + 1}{\sigma} \right) \frac{1}{\sigma} \frac{2}{v_1 + 3} - \frac{v_2 + 1}{\sigma} \frac{1}{\sigma} \frac{2}{v_2 + 3} \\
&= \frac{2}{\sigma^2} \left[ \frac{v_1 + 1}{v_1 + 3} - \frac{v_2 + 1}{v_2 + 3} \right].
\end{aligned}$$

(1). By the symmetry property of  $v_1$  and  $v_2$ , similarly, we have

$$E \left[ \frac{\partial \ln f}{\partial v_2} \right]^2 = -E \left[ \frac{\partial^2 \ln f}{\partial v_2^2} \right] = \frac{1 - \alpha}{2} \left\{ \frac{v_2 D^2(v_2)}{v_2 + 3} - \frac{2D(v_2)}{v_2 + 1} - D'(v_2) \right\};$$

$$\begin{aligned}
E \left[ \frac{\partial \ln f}{\partial v_2} \frac{\partial \ln f}{\partial \alpha} \right] &= -E \left[ \frac{\partial^2 \ln f}{\partial v_2 \partial \alpha} \right] = \frac{1}{v_2 + 1} - \frac{v_2}{v_2 + 3} D(v_2); \\
E \left[ \frac{\partial \ln f}{\partial v_2} \frac{\partial \ln f}{\partial \mu} \right] &= -E \left[ \frac{\partial^2 \ln f}{\partial v_2 \partial \mu} \right] = -\frac{1}{\sigma} \left[ \frac{1}{v_2 + 1} - \frac{v_2 + 1}{v_2 + 3} D(v_2) \right]; \\
E \left[ \frac{\partial \ln f}{\partial v_2} \frac{\partial \ln f}{\partial \sigma} \right] &= -E \left[ \frac{\partial^2 \ln f}{\partial v_2 \partial \sigma} \right] = \frac{1 - \alpha}{\sigma} \left[ -\frac{1}{v_2 + 1} + \frac{v_2 D(v_2)}{v_2 + 3} \right]. \blacksquare
\end{aligned}$$