

Supplement to the paper “Predictive estimation of a covariance matrix and its structural parameters”

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This supplement gives the proofs of the theorems and corollaries in Ogasawara (2017).

A.1 Proof of Theorem 1

We minimize the following with respect to k :

$$\begin{aligned} E^{(S)}(-2\hat{l}^*) &= E^{(S)}\{\ln |\hat{\Sigma}| + \text{tr}(\hat{\Sigma}^{-1}\Sigma_0)\} + E^{(T)}\{C(T)\} \\ &= p \ln k + E^{(S)}\{\ln |S|\} + k^{-1}E^{(S)}\{\text{tr}(S^{-1}\Sigma_0)\} + E^{(S)}\{C(S)\} \\ &= p \ln k + \frac{np}{k(n-p-1)} + \frac{p+1}{n}\{\ln |\Sigma_0| + p \ln(2/n) + \psi_p(n/2)\} \\ &\quad + p \ln(2/n) + \frac{2}{n} \ln \Gamma_p(n/2), \end{aligned} \tag{A1.1}$$

where under normality $E^{(S)}(S^{-1}) = \{n/(n-p-1)\}\Sigma_0^{-1}$ (Anderson, 2003, Lemma 7.7.1) is used. Differentiating (A1.1) with respect to k and setting the result equal to 0, we obtain (2.8).

A.2 Proof of Theorem 2

Noting that $n = N - 1$, the following is minimized with respect to k :

$$\begin{aligned} E^{(X)}(-2\hat{l}^*) &= p \ln(2\pi) + p \ln k + E^{(X)}(\ln |\hat{\Sigma}_{NML}|) \\ &\quad + \text{tr}\{k^{-1}E^{(X)}(\hat{\Sigma}_{NML}^{-1})(\Sigma_0 + N^{-1}\Sigma_0)\} \\ &= p \ln(2\pi) + p \ln k + E^{(X)}(\ln |\hat{\Sigma}_{NML}|) \\ &\quad + k^{-1} \frac{N}{N-1} \frac{n}{n-p-1} (1+N^{-1})p \end{aligned} \tag{A2.1}$$

$$= p \ln k + \frac{(N+1)p}{k(N-p-2)} + p \ln(2\pi) + p \ln \frac{N-1}{N} \\ + \ln |\Sigma_0| + p \ln(2/n) + \psi_p(n/2),$$

where the independence of $\bar{\mathbf{x}}$ and $\hat{\Sigma}_{\text{NML}}$ under normality is used.
Differentiating (A2.1) with respect to k , we obtain (2.17).

A.3 Proof of Theorem 3

First, we have

$$\bar{l} = -\frac{p}{2} \ln(2\pi) - \frac{1}{2} \ln |\Sigma| - \frac{N^{-1}}{2} \sum_{i=1}^N (\mathbf{x}_i - \boldsymbol{\mu})' \Sigma^{-1} (\mathbf{x}_i - \boldsymbol{\mu}) \quad (\text{A3.1})$$

which gives

$$\begin{aligned} \frac{\partial \bar{l}}{\partial \boldsymbol{\theta}_0} &= \left(\frac{\partial \bar{l}}{\partial \boldsymbol{\mu}_0'}, \frac{\partial \bar{l}}{\partial \boldsymbol{\sigma}_0'} \right)', \quad \frac{\partial \bar{l}}{\partial \boldsymbol{\mu}_0} = \Sigma_0^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}_0), \\ \frac{\partial \bar{l}}{\partial \boldsymbol{\sigma}_{0ij}} &= -\frac{2 - \delta_{ij}}{2} \sigma_0^{ij} + \frac{2 - \delta_{ij}}{2} \left(N^{-1} \sum_{a=1}^N \Sigma_0^{-1} (\mathbf{x}_a - \boldsymbol{\mu}_0) (\mathbf{x}_a - \boldsymbol{\mu}_0)' \Sigma_0^{-1} \right)_{ij} \\ (p \geq i \geq j \geq 1), \quad \hat{\boldsymbol{\theta}}_{\text{NML}} &= \left[\bar{\mathbf{x}}', \mathbf{v}' \left\{ N^{-1} \sum_{a=1}^N \Sigma_0^{-1} (\mathbf{x}_a - \bar{\mathbf{x}}) (\mathbf{x}_a - \bar{\mathbf{x}})' \right\} \right]', \\ &= \{\hat{\boldsymbol{\mu}}_{\text{NML}}', \mathbf{v}'(\hat{\Sigma}_{\text{NML}})\}' = (\hat{\boldsymbol{\mu}}_{\text{NML}}', \hat{\boldsymbol{\sigma}}_{\text{NML}}')', \\ \frac{\partial^2 \bar{l}}{\partial \boldsymbol{\theta}_0 \partial \boldsymbol{\theta}_0'} &= \begin{bmatrix} \frac{\partial^2 \bar{l}}{\partial \boldsymbol{\mu}_0 \partial \boldsymbol{\mu}_0'} & \frac{\partial^2 \bar{l}}{\partial \boldsymbol{\mu}_0 \partial \boldsymbol{\sigma}_0'} \\ \frac{\partial^2 \bar{l}}{\partial \boldsymbol{\sigma}_0 \partial \boldsymbol{\mu}_0'} & \frac{\partial^2 \bar{l}}{\partial \boldsymbol{\sigma}_0 \partial \boldsymbol{\sigma}_0'} \end{bmatrix}, \quad \frac{\partial^2 \bar{l}}{\partial \boldsymbol{\mu}_0 \partial \boldsymbol{\mu}_0'} = -\Sigma_0^{-1}, \quad (\text{A3.2}) \end{aligned}$$

$$\begin{aligned}
\frac{\partial^2 \bar{I}}{\partial \boldsymbol{\mu}_0 \partial \sigma_{0ij}} &= -\frac{2-\delta_{ij}}{2} \boldsymbol{\Sigma}_0^{-1} (\mathbf{E}_{ij} + \mathbf{E}_{ji}) \boldsymbol{\Sigma}_0^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}_0) \\
&= -\frac{2-\delta_{ij}}{2} \sum_{(i,j)}^2 (\boldsymbol{\Sigma}_0^{-1})_{\cdot i} \{ \boldsymbol{\Sigma}_0^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}_0) \}_j \quad (p \geq i \geq j \geq 1), \\
\frac{\partial^2 \bar{I}}{\partial \sigma_{0ab} \partial \sigma_{0cd}} &= \frac{1}{4} (2-\delta_{ab})(2-\delta_{cd}) (\sigma_0^{ac} \sigma_0^{bd} + \sigma_0^{ad} \sigma_0^{bc}) \\
&\quad - \frac{1}{4} (2-\delta_{ab})(2-\delta_{cd}) \\
&\quad \times \sum_{(a,b)(c,d)}^2 \sigma_0^{ac} \left\{ N^{-1} \sum_{i=1}^N (\mathbf{x}_i - \boldsymbol{\mu}_0) (\mathbf{x}_i - \boldsymbol{\mu}_0)' \boldsymbol{\Sigma}_0^{-1} \right\}_{db} \\
&\quad (p \geq a \geq b \geq 1; p \geq c \geq d \geq 1),
\end{aligned}$$

where δ_{ij} is the Kronecker delta; $\sigma_{0ij} = (\boldsymbol{\Sigma}_0)_{ij}$ and $\sigma_0^{ij} = (\boldsymbol{\Sigma}_0^{-1})_{ij}$; $(\cdot)_{ij}$ is the (i,j) th element of a matrix; \mathbf{E}_{ij} is the matrix of an appropriate size whose (i,j) th element is 1 with the remaining elements being 0; $\sum_{(i,j)}^{(2)} (\cdot)$ indicates the sum of two quantities exchanging i and j ; $(\cdot)_{\cdot i}$ is the i -th column of a matrix; and $(\cdot)_j$ is the j -th element of a vector.

The non-zero submatrices of \mathbf{I}_0 are given by (A3.2) as follows:

$$(\mathbf{I}_0)_{\boldsymbol{\mu}_0, \boldsymbol{\mu}_0'} = \boldsymbol{\Sigma}_0^{-1}, \quad (\mathbf{I}_0)_{\boldsymbol{\sigma}_0, \boldsymbol{\sigma}_0'} = \frac{1}{2} \mathbf{D}_p' (\boldsymbol{\Sigma}_0^{-1} \otimes \boldsymbol{\Sigma}_0^{-1}) \mathbf{D}_p, \quad (\text{A3.3})$$

where $(\cdot)_{\mathbf{x}, \mathbf{y}'}$ indicates a submatrix of a matrix whose rows and columns correspond to \mathbf{x} and \mathbf{y}' , respectively. The elementwise expression of the last submatrix of (A3.3) is

$$\begin{aligned}
(\mathbf{I}_0)_{\sigma_{0ab}, \sigma_{0cd}} &= \frac{1}{4} (2-\delta_{ab})(2-\delta_{cd}) (\sigma_0^{ac} \sigma_0^{bd} + \sigma_0^{ad} \sigma_0^{bc}) \\
&\quad (p \geq a \geq b \geq 1; p \geq c \geq d \geq 1). \quad (\text{A3.4})
\end{aligned}$$

Equation (A3.3) gives

$$\begin{aligned} N \text{acov}(\hat{\boldsymbol{\theta}}_{\text{NML}}) &= \mathbf{I}_0^{-1}, (\mathbf{I}_0^{-1})_{\mu_0, \mu_0} = \Sigma_0, (\mathbf{I}_0^{-1})_{\sigma_0, \mu_0} = \mathbf{O}, \\ (\mathbf{I}_0^{-1})_{\sigma_0, \sigma_0} &= 2\mathbf{D}_p^+(\Sigma_0 \otimes \Sigma_0)\mathbf{D}_p^+. \end{aligned} \quad (\text{A3.5})$$

where $\text{acov}(\cdot)$ is the asymptotic covariance matrix of order $O(N^{-1})$ for a stochastic vector and \mathbf{O} is a zero matrix. The elementwise expression of the last submatrix is

$$(\mathbf{I}_0^{-1})_{\sigma_{0ab}, \sigma_{0cd}} = \sigma_{0ac}\sigma_{0bd} + \sigma_{0ad}\sigma_{0bc} \quad (p \geq a \geq b \geq 1; p \geq c \geq d \geq 1). \quad (\text{A3.6})$$

From the above results we obtain non-zero elements of $N \mathbb{E}\left(\frac{\partial \bar{l}}{\partial \boldsymbol{\theta}_0} \otimes \mathbf{M}\right)$

in (2.22) as follows:

$$\begin{aligned} N \mathbb{E}\left\{\frac{\partial \bar{l}}{\partial \mu_0} \otimes (\mathbf{M})_{\sigma_{0ab}, \mu_0}\right\} &= -\frac{2-\delta_{ab}}{2} \sum_{(a,b)}^2 (\Sigma_0^{-1})_{a.} (\Sigma_0^{-1})_{b.}, \\ N \mathbb{E}\left\{\frac{\partial \bar{l}}{\partial \sigma_{0ab}} \otimes (\mathbf{M})_{\sigma_{0cd}, \sigma_{0ef}}\right\} &= \frac{1}{8}(2-\delta_{ab})(2-\delta_{cd})(2-\delta_{ef}) \\ &\times N \mathbb{E}\left[\left[\Sigma_0^{-1} \left\{N^{-1} \sum_{i=1}^N (\mathbf{x}_i - \boldsymbol{\mu}_0)(\mathbf{x}_i - \boldsymbol{\mu}_0)' - \Sigma_0\right\} \Sigma_0^{-1}\right]_{ab} \right. \\ &\times \left[2(\sigma_0^{ce}\sigma_0^{fd} + \sigma_0^{cf}\sigma_0^{ed}) \right. \\ &\left. - \sum_{(c,d)}^2 \sum_{(e,f)}^2 \sigma_0^{ce} \left\{N^{-1} \sum_{i=1}^N \Sigma_0^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_0)(\mathbf{x}_i - \boldsymbol{\mu}_0)' \Sigma_0^{-1}\right\}_{fd} \right]_{(A)} \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{8} (2 - \delta_{ab})(2 - \delta_{cd})(2 - \delta_{ef}) \left\{ 2\sigma_0^{ab} (\sigma_0^{ce} \sigma_0^{fd} + \sigma_0^{cf} \sigma_0^{ed}) \right. \\
&\quad \left. - \sum_{g,h=1}^p \sum_{i,j=1}^p \sigma_0^{ag} \sigma_0^{hb} \sum_{(c,d)}^2 \sum_{(e,f)}^2 \sigma_0^{ce} \sigma_0^{fi} \sigma_0^{jd} (\sigma_{0gh} \sigma_{0ij} + \sigma_{0gi} \sigma_{0hj} + \sigma_{0gi} \sigma_{0ih}) \right\} \\
&= \frac{1}{8} (2 - \delta_{ab})(2 - \delta_{cd})(2 - \delta_{ef}) \left\{ 2\sigma_0^{ab} (\sigma_0^{ce} \sigma_0^{fd} + \sigma_0^{cf} \sigma_0^{ed}) \right. \\
&\quad \left. - \sum_{(c,d)}^2 \sum_{(e,f)}^2 \sigma_0^{ce} (\sigma_0^{ab} \sigma_0^{fd} + \sigma_0^{af} \sigma_0^{bd} + \sigma_0^{ad} \sigma_0^{bf}) \right\} \\
&= -\frac{1}{8} (2 - \delta_{ab})(2 - \delta_{cd})(2 - \delta_{ef}) \sum_{(c,d)}^2 \sum_{(e,f)}^2 \sigma_0^{ce} (\sigma_0^{af} \sigma_0^{bd} + \sigma_0^{ad} \sigma_0^{bf}) \quad (\text{A3.7})
\end{aligned}$$

(p ≥ a ≥ b ≥ 1; p ≥ c ≥ d ≥ 1; p ≥ e ≥ f ≥ 1),

where $(\cdot)_a$. is the a -th row of a matrix and $\begin{bmatrix} \cdot \\ \vdots \\ \cdot \end{bmatrix}_{(\text{A})}$ is for ease of finding

correspondence. Note that $N \mathbb{E} \left\{ \frac{\partial \bar{I}}{\partial \boldsymbol{\mu}_0}, \otimes (\mathbf{M})_{\boldsymbol{\mu}_0, \boldsymbol{\sigma}_0} \right\}$ is also non-zero. However, this will not be used. Then, (2.22) becomes

$$\begin{aligned}
\mathbf{k} &= \text{diag}^{-1}(\boldsymbol{\theta}_0) \mathbf{I}_0^{-1} \left\{ N \mathbb{E} \left(\frac{\partial \bar{I}}{\partial \boldsymbol{\theta}_0}, \otimes \mathbf{M} \right) \text{vec}(\mathbf{I}_0^{-1}) + \text{diag}^{-1}(\boldsymbol{\theta}_0) \mathbf{1}_{(q)} \right\} \\
&= \text{diag}^{-1}(\boldsymbol{\mu}_0, \boldsymbol{\sigma}_0)' \begin{bmatrix} \boldsymbol{\Sigma}_0 & \mathbf{O} \\ \mathbf{O} & 2\mathbf{D}_p^+ (\boldsymbol{\Sigma}_0 \otimes \boldsymbol{\Sigma}_0) \mathbf{D}_p^+ \end{bmatrix} \\
&\quad \times \left\{ \begin{pmatrix} \mathbf{0} & (p \times 1) \\ \mathbf{x}_\sigma (p^* \times 1) \end{pmatrix} + \begin{pmatrix} \mathbf{0} & (p \times 1) \\ \mathbf{y}_\sigma (p^* \times 1) \end{pmatrix} + \text{diag}^{-1}(\boldsymbol{\mu}_0, \boldsymbol{\sigma}_0)' \mathbf{1}_{(q)} \right\}, \quad (\text{A3.8})
\end{aligned}$$

where $\mathbf{0} (p \times 1)$ is the $p \times 1$ zero vector; and

$$\begin{aligned}
(\mathbf{x}_\sigma)_{(ef)} &= -\frac{2-\delta_{ef}}{2} (\sigma_0^{ef} + \sigma_0^{fe}) = -(2-\delta_{ef}) \sigma_0^{ef}, \\
(\mathbf{y}_\sigma)_{(ef)} &= \frac{2-\delta_{ef}}{8} \sum_{a,b=1}^p \sum_{c,d=1}^p [-\{\sigma_0^{ce} (\sigma_0^{af} \sigma_0^{bd} + \sigma_0^{ad} \sigma_0^{bf}) + \sigma_0^{de} (\sigma_0^{af} \sigma_0^{bc} + \sigma_0^{ac} \sigma_0^{bf}) \\
&\quad + \sigma_0^{cf} (\sigma_0^{ae} \sigma_0^{bd} + \sigma_0^{ad} \sigma_0^{be}) + \sigma_0^{df} (\sigma_0^{ae} \sigma_0^{bc} + \sigma_0^{ac} \sigma_0^{be}) \}] \\
&\quad \times (\sigma_{0ac} \sigma_{0bd} + \sigma_{0ad} \sigma_{0bc}) \\
&= \frac{2-\delta_{ef}}{8} \{-8(p+1)\sigma_0^{ef}\} = -(2-\delta_{ef})(p+1)\sigma_0^{ef} \quad (p \geq e \geq f \geq 1),
\end{aligned} \tag{A3.9}$$

where $(\cdot)_{(ef)}$ is the element of a vector corresponding to σ_{0ef} using the double subscript notation, and $\sum_{a \geq b} \sum_{c \geq d} (2-\delta_{ab})(2-\delta_{cd})(\cdot) = \sum_{a,b=1}^p \sum_{c,d=1}^p (\cdot)$ is used.

From (A3.9), we have $(\mathbf{x}_\sigma + \mathbf{y}_\sigma)_{(ef)} = -(2-\delta_{ef})(p+2)\sigma_0^{ef}$, which is rewritten as

$$\mathbf{x}_\sigma + \mathbf{y}_\sigma = -(p+2)\mathbf{D}_p' \text{vec}(\Sigma_0^{-1}). \tag{A3.10}$$

From (A3.8) and (A3.10), \mathbf{k}_{μ_0} and \mathbf{k}_{σ_0} in $\mathbf{k} = (\mathbf{k}_{\mu_0}', \mathbf{k}_{\sigma_0}')'$ are

$$\mathbf{k}_{\mu_0} = \text{diag}^{-1}(\boldsymbol{\mu}_0) \Sigma_0 \text{diag}^{-1}(\boldsymbol{\mu}_0) \mathbf{1}_{(p)} \tag{A3.11}$$

and

$$\begin{aligned}
\mathbf{k}_{\sigma_0} &= \text{diag}^{-1}(\boldsymbol{\sigma}_0) 2\mathbf{D}_p^+(\Sigma_0 \otimes \Sigma_0) \mathbf{D}_p^+ \\
&\quad \times \{-(p+2)\mathbf{D}_p' \text{vec}(\Sigma_0^{-1}) + \text{diag}^{-1}(\boldsymbol{\sigma}_0) \mathbf{1}_{(p^*)}\} \\
&= -2(p+2)\text{diag}^{-1}(\boldsymbol{\sigma}_0) \mathbf{D}_p^+ \text{vec}(\Sigma_0) \\
&\quad + 2\text{diag}^{-1}(\boldsymbol{\sigma}_0) \mathbf{D}_p^+(\Sigma_0 \otimes \Sigma_0) \mathbf{D}_p^+ \text{diag}^{-1}(\boldsymbol{\sigma}_0) \mathbf{1}_{(p^*)},
\end{aligned} \tag{A3.12}$$

respectively, where

$$\begin{aligned}
(\Sigma_0 \otimes \Sigma_0) \mathbf{D}_p^+ \mathbf{D}_p' &= \mathbf{D}_p^+ \mathbf{D}_p' (\Sigma_0 \otimes \Sigma_0), \quad \mathbf{D}_p^+ \mathbf{D}_p^+ \mathbf{D}_p' = \mathbf{D}_p^+ \quad \text{and (A3.13)} \\
(\Sigma_0 \otimes \Sigma_0) \text{vec}(\Sigma_0^{-1}) &= \text{vec}(\Sigma_0 \Sigma_0^{-1} \Sigma_0) = \text{vec}(\Sigma_0)
\end{aligned}$$

are used. In (A3.12), noting $\mathbf{D}_p^+ \text{vec}(\boldsymbol{\Sigma}_0) = \boldsymbol{\sigma}_0$, (A3.12) becomes

$$\begin{aligned} \mathbf{k}_{\boldsymbol{\sigma}_0} &= -2(p+2)\mathbf{1}_{(p^*)} \\ &\quad + 2\text{diag}^{-1}(\boldsymbol{\sigma}_0)\mathbf{D}_p^+(\boldsymbol{\Sigma}_0 \otimes \boldsymbol{\Sigma}_0)\mathbf{D}_p^+ \text{diag}^{-1}(\boldsymbol{\sigma}_0)\mathbf{1}_{(p^*)}. \end{aligned} \quad (\text{A3.14})$$

Equations (A3.11) and (A3.14) give (2.25) and (2.26), respectively.

A.4 Proof of Theorem 4

We derive

$$\mathbf{k} = \text{diag}^{-1}(\boldsymbol{\theta}_0)\mathbf{I}_0^{-1} \left\{ nE \left(\frac{\partial \bar{l}}{\partial \boldsymbol{\theta}_0} \otimes \mathbf{M} \right) \text{vec}(\mathbf{I}_0^{-1}) + \text{diag}^{-1}(\boldsymbol{\theta}_0)\mathbf{1}_{(q)} \right\} \quad (\text{A4.1})$$

(see (2.22)). Noting $\bar{l} = -\frac{1}{2}\ln|\boldsymbol{\Sigma}| - \frac{1}{2}\text{tr}(\boldsymbol{\Sigma}^{-1}\mathbf{S}) - \frac{1}{2}C(\mathbf{S})$ (for $C(\mathbf{S})$ see (2.4)), we have

$$\begin{aligned} \frac{\partial \bar{l}}{\partial \theta_{0i}} &= \frac{1}{2}\text{tr} \left\{ \boldsymbol{\Sigma}_0^{-1}(\mathbf{S} - \boldsymbol{\Sigma}_0)\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0i}} \right\}, \\ \frac{\partial^2 \bar{l}}{\partial \theta_{0i} \partial \theta_{0j}} &= -\text{tr} \left\{ \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0j}} \boldsymbol{\Sigma}_0^{-1}(\mathbf{S} - \boldsymbol{\Sigma}_0)\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0i}} \right\} \\ &\quad - \frac{1}{2}\text{tr} \left(\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0j}} \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0i}} \right) \\ &\quad + \frac{1}{2}\text{tr} \left\{ \boldsymbol{\Sigma}_0^{-1}(\mathbf{S} - \boldsymbol{\Sigma}_0)\boldsymbol{\Sigma}_0^{-1} \frac{\partial^2 \boldsymbol{\Sigma}}{\partial \theta_{0i} \partial \theta_{0j}} \right\}, \end{aligned} \quad (\text{A4.2})$$

$$\begin{aligned}
 (\mathbf{M})_{ij} &= \frac{\partial^2 \bar{l}}{\partial \theta_{0i} \partial \theta_{0j}} - E\left(\frac{\partial^2 \bar{l}}{\partial \theta_{0i} \partial \theta_{0j}}\right) = \frac{\partial^2 \bar{l}}{\partial \theta_{0i} \partial \theta_{0j}} + (\mathbf{I}_0)_{ij} \\
 &= -\text{tr}\left\{\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0i}} \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0j}} \boldsymbol{\Sigma}_0^{-1} (\mathbf{S} - \boldsymbol{\Sigma}_0)\right\} \\
 &\quad + \frac{1}{2} \text{tr}\left\{\boldsymbol{\Sigma}_0^{-1} \frac{\partial^2 \boldsymbol{\Sigma}}{\partial \theta_{0i} \partial \theta_{0j}} \boldsymbol{\Sigma}_0^{-1} (\mathbf{S} - \boldsymbol{\Sigma}_0)\right\}
 \end{aligned}$$

($i, j = 1, \dots, q$).

Then, it follows that

$$\begin{aligned}
 nE\left\{\frac{\partial \bar{l}}{\partial \theta_{0a}} (\mathbf{M})_{bc}\right\} &= \frac{1}{4} \text{vec}'\left(\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0a}} \boldsymbol{\Sigma}_0^{-1}\right) n \text{cov}\{\text{vec}(\mathbf{S})\} \\
 &\quad \times \text{vec}\left(-2 \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0b}} \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0c}} \boldsymbol{\Sigma}_0^{-1} + \boldsymbol{\Sigma}_0^{-1} \frac{\partial^2 \boldsymbol{\Sigma}}{\partial \theta_{0b} \partial \theta_{0c}} \boldsymbol{\Sigma}_0^{-1}\right) \\
 &= \frac{1}{2} \text{vec}'\left(\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0a}} \boldsymbol{\Sigma}_0^{-1}\right) \mathbf{\Pi}_p (\boldsymbol{\Sigma}_0 \otimes \boldsymbol{\Sigma}_0) \mathbf{\Pi}_p \\
 &\quad \times \text{vec}\left\{\boldsymbol{\Sigma}_0^{-1} \left(-2 \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0b}} \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0c}} + \frac{\partial^2 \boldsymbol{\Sigma}}{\partial \theta_{0b} \partial \theta_{0c}}\right) \boldsymbol{\Sigma}_0^{-1}\right\} \quad (\text{A4.3}) \\
 &= \frac{1}{2} \text{tr}\left\{\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0a}} \boldsymbol{\Sigma}_0^{-1} \left(-2 \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0b}} \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0c}} + \frac{\partial^2 \boldsymbol{\Sigma}}{\partial \theta_{0b} \partial \theta_{0c}}\right)\right\}
 \end{aligned}$$

($a, b, c = 1, \dots, q$),

where $n \text{cov}\{\text{vec}(\mathbf{S})\} = 2 \mathbf{D}_p (\mathbf{D}_p' \mathbf{D}_p)^{-1} \mathbf{D}_p' (\boldsymbol{\Sigma}_0 \otimes \boldsymbol{\Sigma}_0) \mathbf{D}_p (\mathbf{D}_p' \mathbf{D}_p)^{-1} \mathbf{D}_p'$
 $\equiv 2 \mathbf{\Pi}_p (\boldsymbol{\Sigma}_0 \otimes \boldsymbol{\Sigma}_0) \mathbf{\Pi}_p$ and $\mathbf{\Pi}_p \text{vec}(\mathbf{A}) = \text{vec}(\mathbf{A})$ when $\mathbf{A} = \mathbf{A}'$, are used.

Note that $n \text{cov}\{\text{vec}(\mathbf{S})\}$ under normality is an exact result (see, e.g., Kaplan, 1952, Equation (3)). The (i, j) th element of the information matrix is given by

$$(\mathbf{I}_0)_{ij} = -E\left(\frac{\partial^2 \bar{l}}{\partial \theta_{0i} \partial \theta_{0j}}\right) = \frac{1}{2} \text{tr}\left(\boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0i}} \boldsymbol{\Sigma}_0^{-1} \frac{\partial \boldsymbol{\Sigma}}{\partial \theta_{0j}}\right) \quad (i, j = 1, \dots, q). \text{ The}$$

above results yield (2.29).

A.5 Proof of Corollary 1

First, we derive $nE\left(\frac{\partial \bar{l}}{\partial \boldsymbol{\theta}_0}, \otimes \mathbf{M}\right)$. From (A4.3) with $\frac{\partial^2 \Sigma}{\partial \theta_{0b} \partial \theta_{0c}} = 0$ ($b, c = 1, \dots, p^*$), it follows that

$$\begin{aligned} nE\left\{\frac{\partial \bar{l}}{\partial \sigma_{0ab}} (\mathbf{M})_{cd,ef}\right\} &= -\frac{1}{8}(2-\delta_{ab})(2-\delta_{cd})(2-\delta_{ef}) \\ &\quad \times \text{tr}\{\Sigma_0^{-1}(\mathbf{E}_{ab} + \mathbf{E}_{ba})\Sigma_0^{-1}(\mathbf{E}_{cd} + \mathbf{E}_{dc})\Sigma_0^{-1}(\mathbf{E}_{ef} + \mathbf{E}_{fe})\} \\ &= -\frac{1}{8}(2-\delta_{ab})(2-\delta_{cd})(2-\delta_{ef}) \sum_{(cd,ef)}^4 \sigma_0^{ce}(\sigma_0^{ad}\sigma_0^{bf} + \sigma_0^{af}\sigma_0^{bd}) \\ &\quad (p \geq a \geq b \geq 1; p \geq c \geq d \geq 1; p \geq e \geq f \geq 1). \end{aligned} \quad (\text{A5.1})$$

Using (A5.1), \mathbf{k} is written as

$$\begin{aligned} \mathbf{k} = \text{diag}^{-1}(\boldsymbol{\theta}_0) \sum_{c \geq d} (\mathbf{I}_0^{-1})_{cd} \left[\sum_{a \geq b} \sum_{e \geq f} \left\{ -\frac{1}{8}(2-\delta_{ab})(2-\delta_{cd})(2-\delta_{ef}) \right. \right. \\ \left. \left. \times \sum_{(cd,ef)}^4 \sigma_0^{ce}(\sigma_0^{ad}\sigma_0^{bf} + \sigma_0^{af}\sigma_0^{bd}) \right\} (\mathbf{I}_0^{-1})_{ab,ef} + \frac{1}{\sigma_{0cd}} \right]. \end{aligned} \quad (\text{A5.2})$$

The (gh) -th element of \mathbf{k} in (A5.2) using the double subscript notation is

$$\begin{aligned} (\mathbf{k})_{(gh)} &= \frac{1}{\sigma_{0gh}} \sum_{c \geq d} (\sigma_{0gc}\sigma_{0hd} + \sigma_{0gd}\sigma_{0hc}) \\ &\quad \times \sum_{a \geq b} \sum_{e \geq f} \left\{ -\frac{1}{8}(2-\delta_{ab})(2-\delta_{cd})(2-\delta_{ef}) \right. \\ &\quad \left. \times \sum_{(cd,ef)}^4 \sigma_0^{ce}(\sigma_0^{ad}\sigma_0^{bf} + \sigma_0^{af}\sigma_0^{bd}) \right\} (\sigma_{0ae}\sigma_{0bf} + \sigma_{0af}\sigma_{0be}) \\ &\quad + \frac{1}{\sigma_{0gh}} \sum_{c \geq d} (\sigma_{0gc}\sigma_{0hd} + \sigma_{0gd}\sigma_{0hc}) \frac{1}{\sigma_{0cd}} \end{aligned} \quad (\text{A5.3})$$

$$\begin{aligned}
&= -\frac{1}{8\sigma_{0gh}} \sum_{c,d=1}^p (\sigma_{0gc}\sigma_{0hd} + \sigma_{0gd}\sigma_{0hc}) \sum_{(cd,ef)}^4 (\sigma_0^{cd} p + \sigma_0^{cd} + \sigma_0^{cd} p + \sigma_0^{cd}) \\
&\quad + \frac{1}{\sigma_{0gh}} \sum_{c \geq d} (\sigma_{0gc}\sigma_{0hd} + \sigma_{0gd}\sigma_{0hc}) \frac{1}{\sigma_{0cd}} \\
&= -2(p+1) + \frac{1}{\sigma_{0gh}} \sum_{c \geq d} (\sigma_{0gc}\sigma_{0hd} + \sigma_{0gd}\sigma_{0hc}) \frac{1}{\sigma_{0cd}} \quad (p \geq g \geq h \geq 1).
\end{aligned}$$

A.6 Proof of Theorem 5

Let $E_g^{(S)}(\cdot)$ denote the expectation using the distribution of \mathbf{S} based on the density $g(\mathbf{S} | \cdot)$, which is possibly different from the Wishart density $f(\mathbf{S} | \boldsymbol{\Sigma})$. When obvious a simple notation $E_g(\cdot)$ is also used. Even under non-normality, the following result holds:

$$\begin{aligned}
-2\hat{\bar{l}}^* &= -2E_g^{(T)}\{\bar{l}(\hat{\boldsymbol{\theta}} | \mathbf{T})\} = E_g^{(T)}\{\ln |\hat{\boldsymbol{\Sigma}}| + \text{tr}(\hat{\boldsymbol{\Sigma}}^{-1}\mathbf{T}) + C(\mathbf{T})\} \\
&= \ln |\hat{\boldsymbol{\Sigma}}| + \text{tr}(\hat{\boldsymbol{\Sigma}}^{-1}\boldsymbol{\Sigma}_0) + E_g^{(T)}\{C(\mathbf{T})\}.
\end{aligned} \tag{A6.1}$$

When $\hat{\boldsymbol{\Sigma}} = k\mathbf{S}$, (A6.1) gives

$$E_g^{(S)}(-2\hat{\bar{l}}^*) = p \ln k + E_g(\ln |\mathbf{S}|) + k^{-1}E_g\{\text{tr}(\mathbf{S}^{-1}\boldsymbol{\Sigma}_0)\} + E_g\{C(\mathbf{S})\}. \tag{A6.2}$$

In (A6.2), $E_g(\ln |\mathbf{S}|)$ under arbitrary distributions is given up to order $O(n^{-1})$ using the Taylor series expansion as follows:

$$\begin{aligned}
E_g(\ln |\mathbf{S}|) &= \ln |\boldsymbol{\Sigma}_0| + \frac{n^{-1}}{2} \frac{\partial^2 \ln |\mathbf{S}|}{(\partial \mathbf{s}')^{<2>}}|_{\mathbf{s}=\boldsymbol{\sigma}_0} n E_g\{(\mathbf{s} - \boldsymbol{\sigma}_0)^{<2>}\}_{\rightarrow O(n^{-1})} \\
&\quad + O(n^{-2}),
\end{aligned} \tag{A6.3}$$

where $\mathbf{x}^{<i>} = \mathbf{x} \otimes \dots \otimes \mathbf{x}$ (i times of \mathbf{x});

$$\begin{aligned}
\frac{\partial^2 \ln |\mathbf{S}|}{\partial s_{ab} \partial s_{cd}}|_{\mathbf{s}=\boldsymbol{\sigma}_0} &= \frac{2 - \delta_{ab}}{2} \frac{\partial \text{tr}\{\mathbf{S}^{-1}(\mathbf{E}_{ab} + \mathbf{E}_{ba})\}}{\partial s_{cd}}|_{\mathbf{s}=\boldsymbol{\sigma}_0} \\
&= -\frac{1}{2}(2 - \delta_{ab})(2 - \delta_{cd})(\sigma_0^{ac}\sigma_0^{db} + \sigma_0^{ad}\sigma_0^{cb}) = -2(\boldsymbol{\Omega}_{NT}^{-1})_{ab,cd}; \quad s_{ab} = (\mathbf{S})_{ab} \tag{A6.4} \\
&(p \geq a \geq b \geq 1; \quad p \geq c \geq d \geq 1);
\end{aligned}$$

and $E_g \{\cdot\}_{\rightarrow O(n^{-1})}$ indicates that the expectation is taken up to order $O(n^{-1})$.

Let $\Omega = nE_g \{(\mathbf{s} - \boldsymbol{\sigma}_0)(\mathbf{s} - \boldsymbol{\sigma}_0)'\}_{\rightarrow O(n^{-1})} = \Omega_{NT} + \mathbf{K}_{(4)}$. Then, (A6.3) becomes

$$\begin{aligned} E_g (\ln |\mathbf{S}|) &= \ln |\Sigma_0| - n^{-1} \text{tr}\{\Omega_{NT}^{-1} (\Omega_{NT} + \mathbf{K}_{(4)})\} + O(n^{-2}) \\ &= \ln |\Sigma_0| - n^{-1} \{p^* + \text{tr}(\Omega_{NT}^{-1} \mathbf{K}_{(4)})\} + O(n^{-2}). \end{aligned} \quad (\text{A6.5})$$

On the other hand, $E_g \{\text{tr}(\mathbf{S}^{-1} \Sigma_0)\}$ in (A6.2) is

$$\begin{aligned} E_g \{\text{tr}(\mathbf{S}^{-1} \Sigma_0)\} &= p + \frac{n^{-1}}{2} \frac{\partial^2 \text{tr}(\mathbf{S}^{-1} \Sigma_0)}{\partial \mathbf{s}'^{<2>}} \Big|_{\mathbf{s}=\boldsymbol{\sigma}_0} nE_g \{(\mathbf{s} - \boldsymbol{\sigma}_0)^{<2>}\}_{\rightarrow O(n^{-1})} \\ &\quad + O(n^{-2}), \end{aligned} \quad (\text{A6.6})$$

where

$$\begin{aligned} &\frac{\partial^2 \text{tr}(\mathbf{S}^{-1} \Sigma_0)}{\partial s_{ab} \partial s_{cd}} \Big|_{\mathbf{s}=\boldsymbol{\sigma}_0} \\ &= \frac{1}{2} (2 - \delta_{ab})(2 - \delta_{cd}) \text{tr}\{\Sigma_0^{-1} (\mathbf{E}_{ab} + \mathbf{E}_{ba}) \Sigma_0^{-1} (\mathbf{E}_{cd} + \mathbf{E}_{dc})\} \\ &= (2 - \delta_{ab})(2 - \delta_{cd}) (\sigma_0^{ac} \sigma_0^{db} + \sigma_0^{ad} \sigma_0^{cb}) \\ &\quad (p \geq a \geq b \geq 1; p \geq c \geq d \geq 1). \end{aligned} \quad (\text{A6.7})$$

Consequently, we obtain

$$\begin{aligned} E_g \{\text{tr}(\mathbf{S}^{-1} \Sigma_0)\} &= p + n^{-1} 2 \text{tr}\{\Omega_{NT}^{-1} (\Omega_{NT} + \mathbf{K}_{(4)})\} + O(n^{-2}) \\ &= p + n^{-1} 2 \{p^* + \text{tr}(\Omega_{NT}^{-1} \mathbf{K}_{(4)})\} + O(n^{-2}). \end{aligned} \quad (\text{A6.8})$$

From (A6.5) and (A6.8), (A6.2) becomes

$$\begin{aligned} E_g^{(S)}(-2\hat{l}^*) &= p \ln k + \ln |\Sigma_0| - n^{-1} \{p^* + \text{tr}(\Omega_{NT}^{-1} \mathbf{K}_{(4)})\} \\ &\quad + k^{-1} [p + n^{-1} 2 \{p^* + \text{tr}(\Omega_{NT}^{-1} \mathbf{K}_{(4)})\}] + E_g \{C(\mathbf{S})\} + O(n^{-2}). \end{aligned} \quad (\text{A6.9})$$

Differentiating (A6.9) with respect to k , we obtain

$$k = 1 + n^{-1} \{p + 1 + 2p^{-1} \text{tr}(\Omega_{NT}^{-1} \mathbf{K}_{(4)})\}. \quad (\text{A6.10})$$

Note that for (A6.10), $E_g (\ln |\mathbf{S}|)$ is unnecessary as $E_g \{C(\mathbf{S})\}$ though shown here for later use.

A.7 Proof of Theorem 6

When $k = 1 + n^{-1}\{p + 1 + 2p^{-1}\text{tr}(\boldsymbol{\Omega}_{\text{NT}} + \mathbf{K}_{(4)})\}$, it follows that

$$\begin{aligned}
 E_g^{(S)}(-2\hat{l}^* + 2\hat{l}_{\text{WML}}^*) &= p \ln k + (k^{-1} - 1)E_g\{\text{tr}(\mathbf{S}^{-1}\boldsymbol{\Sigma}_0)\} \\
 &= p \left[n^{-1}\{p + 1 + 2p^{-1}\text{tr}(\boldsymbol{\Omega}_{\text{NT}}^{-1}\mathbf{K}_{(4)})\} \right. \\
 &\quad \left. - \frac{n^{-2}}{2}\{p + 1 + 2p^{-1}\text{tr}(\boldsymbol{\Omega}_{\text{NT}}^{-1}\mathbf{K}_{(4)})\}^2 + O(n^{-3}) \right] \\
 &\quad + \left[-n^{-1}\{p + 1 + 2p^{-1}\text{tr}(\boldsymbol{\Omega}_{\text{NT}}^{-1}\mathbf{K}_{(4)})\} \right. \\
 &\quad \left. + n^{-2}\{p + 1 + 2p^{-1}\text{tr}(\boldsymbol{\Omega}_{\text{NT}}^{-1}\mathbf{K}_{(4)})\}^2 + O(n^{-3}) \right] \\
 &\quad \times [p + n^{-1}2\{p^* + \text{tr}(\boldsymbol{\Omega}_{\text{NT}}^{-1}\mathbf{K}_{(4)})\} + O(n^{-2})] \\
 &= -\frac{n^{-2}}{2}p\{p + 1 + 2p^{-1}\text{tr}(\boldsymbol{\Omega}_{\text{NT}}^{-1}\mathbf{K}_{(4)})\}^2 + O(n^{-3}),
 \end{aligned} \tag{A7.1}$$

which gives (4.8). The result of (4.9) under normality is immediately given from (A7.1) with $\mathbf{K}_{(4)} = \mathbf{O}$. When $k = n/(n-p-1)$, (A7.1) under normality becomes

$$\begin{aligned}
 E_f^{(S)}(-2\hat{l}^* + 2\hat{l}_{\text{WML}}^*) &= p \ln k + (k^{-1} - 1)E_f\{\text{tr}(\mathbf{S}^{-1}\boldsymbol{\Sigma}_0)\} \\
 &= p \ln \frac{n}{n-p-1} + \left(\frac{n-p-1}{n} - 1 \right) \frac{np}{n-p-1} \\
 &= p \ln \frac{n}{n-p-1} - \frac{p(p+1)}{n-p-1},
 \end{aligned} \tag{A7.2}$$

which gives (4.10).

A.8 $E_g^{(S)}(-2\hat{l}^* + 2\hat{l}_0^*)$ when $\hat{\theta} = \hat{\theta}_{\text{WML}}$

Since

$$\begin{aligned} & E_g^{(S)}(-2\hat{l}^* + 2\bar{l}_0^*) \\ &= E_g(\ln |\hat{\Sigma}_{WML}|) - \ln |\Sigma_0| + E_g\{\text{tr}(\hat{\Sigma}_{WML}^{-1}\Sigma_0)\} - p, \end{aligned} \quad (\text{A8.1})$$

the two expectations on the right-hand side of (A8.1) up to order $O(n^{-1})$ are given as follows. Firstly,

$$\begin{aligned} & E_g(\ln |\hat{\Sigma}_{WML}|) \\ &= \ln |\Sigma_0| + \frac{n^{-1}}{2} \frac{\partial^2 \ln |\hat{\Sigma}_{WML}|}{(\partial \mathbf{s}')^{<2>}}|_{\mathbf{s}=\sigma_0} n E_g\{(\mathbf{s} - \sigma_0)^{<2>}\}_{\rightarrow O(n^{-1})} + O(n^{-2}), \end{aligned} \quad (\text{A8.2})$$

where

$$\begin{aligned} \frac{\partial \ln |\hat{\Sigma}_{WML}|}{\partial s_{ab}} &= \sum_{i=1}^q \text{tr} \left\{ \hat{\Sigma}_{WML}^{-1} \frac{\partial \hat{\Sigma}_{WML}}{\partial (\hat{\theta}_{WML})_i} \right\} \frac{\partial (\hat{\theta}_{WML})_i}{\partial s_{ab}}, \\ \frac{\partial^2 \ln |\hat{\Sigma}_{WML}|}{\partial s_{ab} \partial s_{cd}} &= \sum_{i=1}^q \left[\text{tr} \left\{ \hat{\Sigma}_{WML}^{-1} \frac{\partial \hat{\Sigma}_{WML}}{\partial (\hat{\theta}_{WML})_i} \right\} \frac{\partial^2 (\hat{\theta}_{WML})_i}{\partial s_{ab} \partial s_{cd}} \right. \\ &\quad \left. + \sum_{j=1}^q \text{tr} \left\{ \hat{\Sigma}_{WML}^{-1} \frac{\partial^2 \hat{\Sigma}_{WML}}{\partial (\hat{\theta}_{WML})_i \partial (\hat{\theta}_{WML})_j} - \hat{\Sigma}_{WML}^{-1} \frac{\partial \hat{\Sigma}_{WML}}{\partial (\hat{\theta}_{WML})_i} \hat{\Sigma}_{WML}^{-1} \frac{\partial \hat{\Sigma}_{WML}}{\partial (\hat{\theta}_{WML})_j} \right\} \right. \\ &\quad \left. \times \frac{\partial (\hat{\theta}_{WML})_i}{\partial s_{ab}} \frac{\partial (\hat{\theta}_{WML})_j}{\partial s_{ab}} \right] \quad (p \geq a \geq b \geq 1; p \geq c \geq d \geq 1). \end{aligned} \quad (\text{A8.3})$$

In (A8.3), $\frac{\partial (\hat{\theta}_{WML})_i}{\partial s_{ab}}$ and

$\frac{\partial^2 (\hat{\theta}_{WML})_i}{\partial s_{ab} \partial s_{cd}}$ ($i = 1, \dots, q$; $p \geq a \geq b \geq 1$; $p \geq c \geq d \geq 1$) are given by the

formulas for partial derivatives in implicit functions (Ogasawara, 2009, Equation (3.16)).

Secondly,

$$\begin{aligned} & E_g\{\text{tr}(\hat{\Sigma}_{WML}^{-1}\Sigma_0)\} \\ &= p + \frac{n^{-1}}{2} \frac{\partial^2 \{\text{tr}(\hat{\Sigma}_{WML}^{-1}\Sigma_0)\}}{(\partial \mathbf{s}')^{<2>}}|_{\mathbf{s}=\sigma_0} n E_g\{(\mathbf{s} - \sigma_0)^{<2>}\}_{\rightarrow O(n^{-1})} + O(n^{-2}), \end{aligned} \quad (\text{A8.4})$$

where

$$\begin{aligned} \frac{\partial^2 \text{tr}(\hat{\Sigma}_{\text{WML}}^{-1} \Sigma_0)}{\partial s_{ab}} &= \sum_{i=1}^q \left[-\text{tr} \left\{ \hat{\Sigma}_{\text{WML}}^{-1} \frac{\partial \hat{\Sigma}_{\text{WML}}}{\partial (\hat{\theta}_{\text{WML}})_i} \hat{\Sigma}_{\text{WML}}^{-1} \Sigma_0 \right\} \frac{\partial (\hat{\theta}_{\text{WML}})_i}{\partial s_{ab}} \right], \\ \frac{\partial^2 \text{tr}(\hat{\Sigma}_{\text{WML}}^{-1} \Sigma_0)}{\partial s_{ab} \partial s_{cd}} &= \sum_{i=1}^q \left[-\text{tr} \left\{ \hat{\Sigma}_{\text{WML}}^{-1} \frac{\partial \hat{\Sigma}_{\text{WML}}}{\partial (\hat{\theta}_{\text{WML}})_i} \hat{\Sigma}_{\text{WML}}^{-1} \Sigma_0 \right\} \frac{\partial^2 (\hat{\theta}_{\text{WML}})_i}{\partial s_{ab} \partial s_{cd}} \right. \\ &\quad \left. + \sum_{j=1}^q \text{tr} \left\{ -\hat{\Sigma}_{\text{WML}}^{-1} \frac{\partial^2 \hat{\Sigma}_{\text{WML}}}{\partial (\hat{\theta}_{\text{WML}})_i \partial (\hat{\theta}_{\text{WML}})_j} \hat{\Sigma}_{\text{WML}}^{-1} \Sigma_0 \right\} \right] \\ &\quad + 2 \hat{\Sigma}_{\text{WML}}^{-1} \frac{\partial \hat{\Sigma}_{\text{WML}}}{\partial (\hat{\theta}_{\text{WML}})_i} \hat{\Sigma}_{\text{WML}}^{-1} \frac{\partial \hat{\Sigma}_{\text{WML}}}{\partial (\hat{\theta}_{\text{WML}})_j} \hat{\Sigma}_{\text{WML}}^{-1} \Sigma_0 \left. \frac{\partial (\hat{\theta}_{\text{WML}})_i}{\partial s_{ab}} \frac{\partial (\hat{\theta}_{\text{WML}})_j}{\partial s_{ab}} \right] \end{aligned} \quad (\text{A8.5})$$

($p \geq a \geq b \geq 1; p \geq c \geq d \geq 1$).

From (A8.2) with (A8.3) and (A8.4) with (A8.5), (A8.1) is written as

$$\begin{aligned} E_g^{(S)}(-2\hat{l}_* + 2\bar{l}_0^*) &= \frac{n^{-1}}{2} \text{tr} \left\{ \left(\frac{\partial^2 \ln |\hat{\Sigma}_{\text{WML}}|}{\partial s \partial s'} \Big|_{s=\sigma_0} + \frac{\partial^2 \text{tr}(\hat{\Sigma}_{\text{WML}}^{-1} \Sigma_0)}{\partial s \partial s'} \Big|_{s=\sigma_0} \right) \Omega \right\} + O(n^{-2}). \end{aligned} \quad (\text{A8.6})$$

A.9 Proof of Theorem 7

The result of (4.13) is given by

$$-2\hat{l}_{\text{WML}}^* = -2\bar{l}_0^* - \frac{\partial^2 \bar{l}^*}{(\partial \theta_0')^{<2>}} (\hat{\theta}_{\text{WML}} - \theta_0)^{<2>} + O_p(n^{-3/2}), \quad (\text{A9.1})$$

where $\bar{l}^* = E_f^{(T)} \{ \bar{l}(\theta | \mathbf{T}) \}$ and

$$\partial^2 \bar{l}^* / (\partial \theta_0')^{<2>} = \partial^2 \bar{l}^* / (\partial \theta')^{<2>} \Big|_{\theta=\theta_0} = -\text{vec}'(\mathbf{I}_0). \quad \text{On the other hand,}$$

$$E_f^{(S)}(\hat{\theta}_{\text{WML}} - \theta_0)^{<2>} = n^{-1} \text{vec}(\mathbf{I}_0^{-1}) + O(n^{-2}). \quad \text{These results give}$$

$$E_f^{(S)}(-2\hat{l}_{\text{WML}}^*) = -2\bar{l}_0^* + n^{-1} \text{vec}(\mathbf{I}_0) \text{vec}(\mathbf{I}_0^{-1}) + O(n^{-2}) = -2\bar{l}_0^* + n^{-1} q + O(n^{-2}).$$

The unchanged result up to order $O(n^{-1})$ of (4.14) is given by a special case of Ogasawara (2017, Equation (3.9)).

A.10 Proof of Theorem 8

Since the second term on the right-hand side of (6.2) is irrelevant to k_{ij} ,

the expectation of the first term, i.e., $E_g^{(S)} \left\{ \sum_{i \geq j} w_{ij} (k_{ij} s_{ij} - \sigma_{0ij})^2 \right\}$ is

minimized. Noting that

$$\begin{aligned} & E_g^{(S)} \left\{ \sum_{i \geq j} w_{ij} (k_{ij} s_{ij} - \sigma_{0ij})^2 \right\} \\ &= E_g^{(S)} \left\{ \sum_{i \geq j} w_{ij} k_{ij}^2 (s_{ij} - \sigma_{0ij})^2 \right\} + \sum_{i \geq j} w_{ij} (k_{ij} - 1)^2 \sigma_{0ij}^2 \\ &= \sum_{i \geq j} w_{ij} \text{var}(s_{ij}) k_{ij}^2 + \sum_{i \geq j} w_{ij} (k_{ij} - 1)^2 \sigma_{0ij}^2, \end{aligned} \quad (\text{A10.1})$$

the minimizing constant k_{ij} is given by

$$k_{ij} = \frac{\sigma_{0ij}^2}{\text{var}(s_{ij}) + \sigma_{0ij}^2} = \frac{1}{1 + c_V^2(s_{ij})} \quad (p \geq i \geq j \geq 1), \quad (\text{A10.2})$$

which gives (6.3) with (6.4).

A.11 Proof of Theorem 9

From (6.18), we obtain

$$\begin{aligned} F &\equiv E^{(X)}(-2\hat{l}^*) = p \ln(2\pi) + E^{(X)}(\ln |\hat{\Sigma}|) \\ &+ \text{tr} \left[E^{(X)}(\hat{\Sigma}^{-1}) [\Sigma_0 + E^{(X)} \{ (\text{diag}(\mathbf{k})(\bar{\mathbf{x}} - \boldsymbol{\mu}_0) + \text{diag}(\mathbf{k})\boldsymbol{\mu}_0 - \boldsymbol{\mu}_0) \right. \\ &\quad \times (\text{diag}(\mathbf{k})(\bar{\mathbf{x}} - \boldsymbol{\mu}_0) + \text{diag}(\mathbf{k})\boldsymbol{\mu}_0 - \boldsymbol{\mu}_0)' \}] \left. \right] \quad (\text{A11.1}) \end{aligned}$$

$$\begin{aligned} &= p \ln(2\pi) + E^{(X)}(\ln |\hat{\Sigma}|) + \text{tr} \left[E^{(X)}(\hat{\Sigma}^{-1}) \right. \\ &\quad \times [\Sigma_0 + N^{-1} \text{diag}(\mathbf{k})\Sigma_0 \text{diag}(\mathbf{k}) + \{ \text{diag}(\mathbf{k})\boldsymbol{\mu}_0 - \boldsymbol{\mu}_0 \} \{ \text{diag}(\mathbf{k})\boldsymbol{\mu}_0 - \boldsymbol{\mu}_0 \}'] \left. \right], \end{aligned}$$

where the independence of $\hat{\Sigma}$ and $\bar{\mathbf{x}}$ under normality is used. Since when $\hat{\Sigma} = c_N^{-1} \sum_{i=1}^N (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})'$, we have

$$E(\hat{\Sigma}^{-1}) = \frac{c_N}{n - p - 1} \Sigma_0^{-1} = \frac{c_N}{N - p - 2} \Sigma_0^{-1} \quad (\text{A11.2})$$

(see Subsection A.1), (A11.1) becomes

$$\begin{aligned}
F &\equiv p \ln(2\pi) + E^{(X)}(\ln |\hat{\Sigma}|) \\
&+ \frac{c_N}{N-p-2} [p + N^{-1} \text{tr}\{\Sigma_0^{-1} \text{diag}(\mathbf{k}) \Sigma_0 \text{diag}(\mathbf{k})\} \\
&+ \{\text{diag}(\mathbf{k}) \boldsymbol{\mu}_0 - \boldsymbol{\mu}_0\}' \Sigma_0^{-1} \{\text{diag}(\mathbf{k}) \boldsymbol{\mu}_0 - \boldsymbol{\mu}_0\}] \\
&= p \ln(2\pi) + E^{(X)}(\ln |\hat{\Sigma}|) \\
&+ \frac{c_N}{N-p-2} \{p + N^{-1} \sum_{i,j=1}^p \sigma_{0ij} \sigma_0^{ij} k_i k_j \\
&+ \mathbf{k}' \text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \text{diag}(\boldsymbol{\mu}_0) \mathbf{k} - 2\boldsymbol{\mu}_0' \Sigma_0^{-1} \text{diag}(\boldsymbol{\mu}_0) \mathbf{k} + \boldsymbol{\mu}_0' \Sigma_0^{-1} \boldsymbol{\mu}_0\}. \tag{A11.3}
\end{aligned}$$

Differentiating (A11.3) with respect to \mathbf{k} and setting the result to a zero vector, we have

$$\begin{aligned}
\frac{N-p-2}{c_N} \frac{\partial F}{\partial \mathbf{k}} &= 2N^{-1} \text{Diag}\{\Sigma_0^{-1} \text{diag}(\mathbf{k}) \Sigma_0\} \mathbf{1}_{(p)} \\
&+ 2\text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \text{diag}(\boldsymbol{\mu}_0) \mathbf{k} - 2\text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \boldsymbol{\mu}_0 = \mathbf{0}. \tag{A11.4}
\end{aligned}$$

Since the left-hand side of the last equation of (A11.4) is

$$\begin{aligned}
&2 \left\{ N^{-1} \begin{pmatrix} \sigma_{011} \sigma_0^{11} & \sigma_{021} \sigma_0^{21} \cdots \sigma_{01p} \sigma_0^{1p} \\ \sigma_{021} \sigma_0^{21} & \sigma_{022} \sigma_0^{22} \cdots \sigma_{02p} \sigma_0^{2p} \\ \vdots & \vdots \ddots \vdots \\ \sigma_{0p1} \sigma_0^{p1} & \sigma_{0p2} \sigma_0^{p2} \cdots \sigma_{0pp} \sigma_0^{pp} \end{pmatrix} + \text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \text{diag}(\boldsymbol{\mu}_0) \right\} \mathbf{k} \\
&- 2\text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \boldsymbol{\mu}_0 \\
&= 2\{N^{-1} \Sigma_0 \odot \Sigma_0^{-1} + \text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \text{diag}(\boldsymbol{\mu}_0)\} \mathbf{k} - 2\text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \boldsymbol{\mu}_0, \tag{A11.5}
\end{aligned}$$

we obtain

$$\mathbf{k} = \{N^{-1} \Sigma_0 \odot \Sigma_0^{-1} + \text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \text{diag}(\boldsymbol{\mu}_0)\}^{-1} \text{diag}(\boldsymbol{\mu}_0) \Sigma_0^{-1} \boldsymbol{\mu}_0. \tag{A11.6}$$

A.12 Proof of Corollary 3

Equation (6.23) becomes

$$\begin{aligned}
\text{PGMSE} &= E^{(X)} \{(\hat{\boldsymbol{\mu}}_k^{(P)} - \boldsymbol{\mu}_0)' \Sigma_0^{-1} (\hat{\boldsymbol{\mu}}_k^{(P)} - \boldsymbol{\mu}_0)\} + N^{-1} p \\
&\equiv \text{GMSE} + N^{-1} p, \tag{A12.1}
\end{aligned}$$

which shows that minimizing PGMSE is equivalent to minimizing GMSE.

From $\hat{\boldsymbol{\mu}}_k^{(P)} = \text{diag}(\mathbf{k}) \bar{\mathbf{x}}$, GMSE is

$$\begin{aligned}
 \text{GMSE} &= E^{(X)}[\{\text{diag}(\mathbf{k})\bar{\mathbf{x}} - \boldsymbol{\mu}_0\}'\boldsymbol{\Sigma}_0^{-1}\{\text{diag}(\mathbf{k})\bar{\mathbf{x}} - \boldsymbol{\mu}_0\}] \\
 &= N^{-1}\text{tr}\{\text{diag}(\mathbf{k})\boldsymbol{\Sigma}_0^{-1}\text{diag}(\mathbf{k})\boldsymbol{\Sigma}_0\} \\
 &\quad + \{\text{diag}(\mathbf{k})\boldsymbol{\mu}_0 - \boldsymbol{\mu}_0\}'\boldsymbol{\Sigma}_0^{-1}\{\text{diag}(\mathbf{k})\boldsymbol{\mu}_0 - \boldsymbol{\mu}_0\}.
 \end{aligned} \tag{A12.2}$$

Since F in (A11.3) is an affine transformation of (A12.2) and consequently (A12.1), the result of the corollary follows.

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