

Local Linear Estimation of Covariance Matrices via Cholesky Decomposition

Ziqi Chen and Chenlei Leng

Central South University and University of Warwick

Supplementary Material

Lemma 1. *Under conditions (a)–(d), we have*

$$\hat{m}(u) - m(u) = \frac{1}{2} \mu_2 h^2 m''(u) + \frac{1}{n f(u)} \sum_{i=1}^n K_h(U_i - u) \{Y_i - m(U_i)\} + o_p(c_n),$$

which holds uniformly in u .

Lemma 2. *If conditions (a)–(d) hold, we have*

$$\frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n K_h(U_i - u) K_h(U_j - U_i) \frac{r_{ik} r_{jq}}{f(U_i)} = o_p(c_n),$$

which holds uniformly in u , for $k, q = 1, \dots, p$.

Proof: We have

$$\begin{aligned} & \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n K_h(U_i - u) K_h(U_j - U_i) \frac{r_{ik} r_{jq}}{f(U_i)} \\ &= \frac{n(n-1)}{n^2} \frac{1}{n(n-1)} \sum_{i \neq j} K_h(U_i - u) K_h(U_j - U_i) \frac{r_{ik} r_{jq}}{f(U_i)} + \frac{K(0)}{nh} \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) \frac{r_{ik} r_{iq}}{f(U_i)}. \end{aligned}$$

Note $\mathcal{F} = \{\frac{1}{n(n-1)} \sum_{i \neq j} K(\frac{U_i - u}{h}) K(\frac{U_j - U_i}{h}) \frac{r_{ik} r_{jq}}{f(U_i)} : u \in \Omega\}$ is a U-process of order 2 indexed by Ω . We know easily that $K(\frac{U_i - u}{h}) K(\frac{U_j - U_i}{h}) \frac{r_{ik} r_{jq}}{f(U_i)}$ is P-degenerate for each $u \in \Omega$. From

Lemma 2.13 in Pakes and Pollard (1989), \mathcal{F} is Euclidean for some envelope F satisfying $E(F^2) < \infty$. Thus, by Corollary 4 in Sherman (1994), the first term of the right-hand side of the above equation is $O_p(1/(nh^2))$ uniformly in u . It can be easily seen that the second term of the right-hand side of the above equation is $O_p(1/(nh))$ uniformly in u . Thus, the result follows immediately.

Proof of Theorem 1: Firstly, we have

$$\begin{aligned} \hat{\Phi}_j(u) - \Phi_j(u) &= (I_{(j-1)}, \mathbf{0}_{(j-1)}) \left\{ \sum_{i=1}^n K_h(U_i - u) X_i^{(j)T} X_i^{(j)} \right\}^{-1} \\ &\quad \times \sum_{i=1}^n K_h(U_i - u) X_i^{(j)T} \{ \hat{r}_{ij} - \sum_{l=1}^{j-1} \hat{r}_{il} \phi_{jl}(u) - \sum_{l=1}^{j-1} \hat{r}_{il} \phi'_{jl}(u)(U_i - u) \}. \end{aligned} \quad (1)$$

By Lemma 1 and Lemma 2, we have

$$\begin{aligned} \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) \hat{r}_{ik} \hat{r}_{iq} &= \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) [r_{ik} - \{\hat{m}_k(U_i) - m_k(U_i)\}] [r_{iq} - \{\hat{m}_q(U_i) - m_q(U_i)\}] \\ &= \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) r_{ik} r_{iq} - \frac{\mu_2 h^2}{2n} \sum_{i=1}^n K_h(U_i - u) [m''_k(U_i) r_{iq} + m''_q(U_i) r_{ik}] \\ &\quad - \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n K_h(U_i - u) K_h(U_j - U_i) \frac{r_{ik} r_{jq}}{f(U_i)} \\ &\quad - \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n K_h(U_i - u) K_h(U_j - U_i) \frac{r_{jk} r_{iq}}{f(U_i)} + o_p(c_n) \\ &= \sigma_{kq}(u) f(u) + o_p(1), \end{aligned} \quad (2)$$

which holds uniformly in u , where $\sigma_{kq}(u)$ is the (k, q) -th entry of $\Sigma(u)$. And we have that the following two equations hold uniformly in u :

$$\frac{1}{n} \sum_{i=1}^n K_h(U_i - u) (U_i - u) \hat{r}_{ik} \hat{r}_{iq} = O_p(h^2), \quad (3)$$

$$\frac{1}{n} \sum_{i=1}^n K_h(U_i - u) (U_i - u)^2 \hat{r}_{ik} \hat{r}_{iq} = O_p(h^2) \quad (4)$$

We can see easily that

$$\begin{aligned}
& \hat{r}_{ij} - \sum_{l=1}^{j-1} \hat{r}_{il} \phi_{jl}(u) - \sum_{l=1}^{j-1} \hat{r}_{il} \phi'_{jl}(u)(U_i - u) \\
&= \epsilon_{ij} + \frac{1}{2}[(U_i - u)^2 r_{i1}, \dots, (U_i - u)^2 r_{i(j-1)}] \Phi_j''(u) + O_p((U_i - u)^3) - (\hat{m}_j(U_i) - m_j(U_i)) \\
&\quad - \sum_{l=1}^{j-1} \phi_{jl}(u)(\hat{m}_l(U_i) - m_l(U_i)) - (U_i - u) \sum_{l=1}^{j-1} \phi'_{jl}(u)(\hat{m}_l(U_i) - m_l(U_i)),
\end{aligned} \tag{5}$$

and

$$X_i^{(j)T} = \begin{pmatrix} r_{i1} - (\hat{m}_1(U_i) - m_1(U_i)) \\ \vdots \\ r_{i(j-1)} - (\hat{m}_{j-1}(U_i) - m_{j-1}(U_i)) \\ (U_i - u)\{r_{i1} - (\hat{m}_1(U_i) - m_1(U_i))\} \\ \vdots \\ (U_i - u)\{r_{i(j-1)} - (\hat{m}_{j-1}(U_i) - m_{j-1}(U_i))\} \end{pmatrix}. \tag{6}$$

By (5) and (6), using Lemma 1 and Lemma 2, we have

$$\begin{aligned}
& \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) X_i^{(j)T} \left\{ \hat{r}_{ij} - \sum_{l=1}^{j-1} \hat{r}_{il} \phi_{jl}(u) - \sum_{l=1}^{j-1} \hat{r}_{il} \phi'_{jl}(u)(U_i - u) \right\} \\
&= \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) \begin{pmatrix} r_{i1} \\ \vdots \\ r_{i(j-1)} \\ (U_i - u)r_{i1} \\ \vdots \\ (U_i - u)r_{i(j-1)} \end{pmatrix} \left\{ \epsilon_{ij} + \frac{1}{2}[(U_i - u)^2 r_{i1}, \dots, (U_i - u)^2 r_{i(j-1)}] \Phi_j''(u) \right\} \\
&\quad + o_p(c_n),
\end{aligned} \tag{7}$$

which holds uniformly in u .

By Equations (1), (2), (3), (4) and (7) and the formula of the inverse of a block matrix, we obtain the result through simple calculations.

Proof of Theorem 2: Note that $\nu(u) = \log(\sigma_j^2(u))$. Using the same arguments in the proof

of Theorem 1, we have that

$$\begin{aligned}
\hat{\nu}(u) - \nu(u) &= \frac{1}{nf(u)} \sum_{i=1}^n K_h(U_i - u) \left\{ \hat{\epsilon}_{ij}^2 \exp\{-\nu(u) - \nu'(u)(U_i - u)\} - 1 \right\} \\
&= \frac{1}{nf(u)} \sum_{i=1}^n K_h(U_i - u) \left\{ \hat{\epsilon}_{ij}^2 \exp\{-\nu(U_i) + \frac{1}{2}\nu''(u)(U_i - u)^2 + O_p((U_i - u)^3)\} - 1 \right\} \\
&= \frac{1}{nf(u)} \sum_{i=1}^n K_h(U_i - u) \left\{ \hat{\epsilon}_{ij}^2 \exp\{-\nu(U_i)\} \left\{ 1 + \frac{1}{2}\nu''(u)(U_i - u)^2 \right\} - 1 \right\} + o_p(h^2) \\
&= \frac{1}{nf(u)} \sum_{i=1}^n K_h(U_i - u) \left\{ \hat{\epsilon}_{ij}^2 \exp\{-\nu(U_i)\} - 1 \right\} \\
&\quad + \frac{\nu''(u)}{2nf(u)} \sum_{i=1}^n K_h(U_i - u) \hat{\epsilon}_{ij}^2 \exp\{-\nu(U_i)\} (U_i - u)^2 + o_p(h^2) \\
&= \frac{1}{nf(u)} \sum_{i=1}^n K_h(U_i - u) \left\{ \epsilon_{ij}^2 \exp\{-\nu(U_i)\} - 1 \right\} \\
&\quad + \frac{\nu''(u)}{2nf(u)} \sum_{i=1}^n K_h(U_i - u) \epsilon_{ij}^2 \exp\{-\nu(U_i)\} (U_i - u)^2 + o_p(c_n),
\end{aligned}$$

which holds uniformly in u . By Taylor's expansion, it can be easily seen that

$$\begin{aligned}
\hat{\sigma}_j^2(u) - \sigma_j^2(u) &= \exp(\hat{\nu}(u)) - \exp(\nu(u)) \\
&= \frac{[\log\{\sigma_j^2(u)\}]'' \sigma_j^2(u)}{2nf(u)} \sum_{i=1}^n K_h(U_i - u) \frac{\epsilon_{ij}^2}{\sigma_j^2(U_i)} (U_i - u)^2 \\
&\quad + \frac{\sigma_j^2(u)}{nf(u)} \sum_{i=1}^n K_h(U_i - u) \left\{ \frac{\epsilon_{ij}^2}{\sigma_j^2(U_i)} - 1 \right\} + o_p(c_n) \\
&= \frac{1}{2} \mu_2 [\log\{\sigma_j^2(u)\}]'' \sigma_j^2(u) h^2 + f^{-1}(u) \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) \left\{ \epsilon_{ij}^2 - \sigma_j^2(U_i) \right\} + o_p(c_n)
\end{aligned}$$

holds uniformly in u .

Proof of Theorem 3: Let $P_B(u) := -2^{-1}\mu_2 h^2 P''(u)$ and $P_V(u)$ a strictly lower triangular matrix with 0's on its diagonal and with the lower triangular vector of its j -th row being

$$f^{-1}(u) \{ \Sigma(u)_{(j-1,j-1)} \}^{-1} \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) (r_{i1}, \dots, r_{i(j-1)}) \epsilon_{ij}.$$

Let $D_B(u)$ and $D_V(u)$ be both diagonal matrices with the j -th diagonal entry being $\sigma_{jB}^2 :=$

$2^{-1}\mu_2 h^2 [\log\{\sigma_j^2(u)\}]'' \sigma_j^2(u)$ and $\sigma_{jV}^2 := (nf(u))^{-1} \sum_{i=1}^n K_h(U_i - u)(\epsilon_{ij}^2 - \sigma_j^2(U_i))$, respectively.

We recall that $\Sigma(u) = P^{-1}(u)D(u)P^{-1}(u)^T$ and

$$\begin{aligned}\hat{\Sigma}^{-1}(u) &= \hat{P}(u)^T \hat{D}^{-1}(u) \hat{P}(u) \\ &= \{P(u) + P_B(u) + P_V(u)\}^T \{D(u) + D_B(u) + D_V(u)\}^{-1} \{P(u) + P_B(u) + P_V(u)\}.\end{aligned}$$

Since

$$\begin{aligned}\{D(u) + D_B(u) + D_V(u)\}^{-1} &= D^{-1}(u) - D^{-2}(u)\{D_B(u) + D_V(u)\} \\ &\quad + 2D^{-3}(u)\{D_B(u) + D_V(u)\}^2 + o_p(h^4 + \frac{1}{nh}),\end{aligned}$$

we have

$$\begin{aligned}\hat{\Sigma}^{-1}(u) &= \{P(u) + P_B(u) + P_V(u)\}^T \left[D^{-1}(u) - D^{-2}(u)\{D_B(u) + D_V(u)\} \right. \\ &\quad \left. + 2D^{-3}(u)\{D_B(u) + D_V(u)\}^2 \right] \{P(u) + P_B(u) + P_V(u)\} + o_p(h^4 + \frac{1}{nh}) \\ &= P(u)^T D^{-1}(u) P(u) + \{P_B(u) + P_V(u)\}^T D^{-1}(u) P(u) + P(u)^T D^{-1}(u) \{P_B(u) + P_V(u)\} \\ &\quad + \{P_B(u) + P_V(u)\}^T D^{-1}(u) \{P_B(u) + P_V(u)\} \\ &\quad - \left[P(u)^T D^{-2}(u) \{D_B(u) + D_V(u)\} P(u) \right. \\ &\quad \left. + P(u)^T D^{-2}(u) \{D_B(u) + D_V(u)\} \{P_B(u) + P_V(u)\} \right. \\ &\quad \left. + \{P_B(u) + P_V(u)\}^T D^{-2}(u) \{D_B(u) + D_V(u)\} P(u) \right. \\ &\quad \left. + \{P_B(u) + P_V(u)\}^T D^{-2}(u) \{D_B(u) + D_V(u)\} \{P_B(u) + P_V(u)\} \right] \\ &\quad + 2 \left[P(u)^T D^{-3}(u) \{D_B(u) + D_V(u)\}^2 P(u) \right. \\ &\quad \left. + P(u)^T D^{-3}(u) \{D_B(u) + D_V(u)\}^2 \{P_B(u) + P_V(u)\} \right. \\ &\quad \left. + \{P_B(u) + P_V(u)\}^T D^{-3}(u) \{D_B(u) + D_V(u)\}^2 P(u) \right. \\ &\quad \left. + \{P_B(u) + P_V(u)\}^T D^{-3}(u) \{D_B(u) + D_V(u)\}^2 \{P_B(u) + P_V(u)\} \right] + o_p(h^4 + \frac{1}{nh}).\end{aligned}$$

Thus, we obtain

$$\begin{aligned}
\text{trace}(\Sigma(u)\hat{\Sigma}^{-1}(u)) &= p + \text{trace}\left[\{P_B(u) + P_V(u)\}^T\{P_B(u) + P_V(u)\}P^{-1}(u)P^{-1}(u)^T\right] \\
&\quad - \text{trace}\left[D^{-1}(u)\{D_B(u) + D_V(u)\}\right] + 2\text{trace}\left[D^{-2}(u)\{D_B(u) + D_V(u)\}^2\right] \\
&\quad + o_p(h^4 + \frac{1}{nh}) \\
&= p + \text{trace}\left[\{P_B(u) + P_V(u)\}^T\{P_B(u) + P_V(u)\}P^{-1}(u)P^{-1}(u)^T\right] \\
&\quad + \sum_{j=1}^p \left[-\frac{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)}{\sigma_j^2(u)} + 2\frac{\{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)\}^2}{(\sigma_j^2(u))^2} \right] + o_p(h^4 + \frac{1}{nh}) \quad (8)
\end{aligned}$$

and

$$\begin{aligned}
\log|\Sigma(u)\hat{\Sigma}^{-1}(u)| &= \log|I - D^{-1}(u)\{D_B(u) + D_V(u)\} + 2D^{-2}(u)\{D_B(u) + D_V(u)\}^2| \\
&\quad + o_p(h^4 + \frac{1}{nh}) \\
&= \sum_{j=1}^p \log\left\{1 - \frac{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)}{\sigma_j^2(u)} + 2\frac{\{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)\}^2}{(\sigma_j^2(u))^2}\right\} + o_p(h^4 + \frac{1}{nh}) \\
&= \sum_{j=1}^p \left[-\frac{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)}{\sigma_j^2(u)} + 2\frac{\{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)\}^2}{(\sigma_j^2(u))^2} - \frac{\{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)\}^2}{2(\sigma_j^2(u))^2} \right] \\
&\quad + o_p(h^4 + \frac{1}{nh}). \quad (9)
\end{aligned}$$

By Equation (8) and (9), we have

$$\begin{aligned}
L(\Sigma(u), \hat{\Sigma}(u))_{KL} &= E\left[\text{trace}[\{P_B(u) + P_V(u)\}^T\{P_B(u) + P_V(u)\}P^{-1}(u)P^{-1}(u)^T]\right. \\
&\quad \left.+ \sum_{j=1}^p \frac{\{\sigma_{jB}^2(u) + \sigma_{jV}^2(u)\}^2}{2(\sigma_j^2(u))^2}\right] + o(h^4 + \frac{1}{nh}) \\
&= \frac{1}{4}\mu_2^2 h^4 \text{trace}\left\{P''(u)^T P''(u) P^{-1}(u) P^{-1}(u)^T + \frac{1}{2}[\{\log D(u)\}'']^2\right\} \\
&\quad + \frac{\int K^2(y)dy}{nhf(u)} \text{trace}\left\{P^*(u)P^{-1}(u)P^{-1}(u)^T + I\right\} + o(h^4 + \frac{1}{nh}),
\end{aligned}$$

which establishes the first equation of Theorem 3. Since

$$\begin{aligned}
L(\Sigma(u), \hat{\Sigma}(u))_F &= E \left[\text{trace} \left\{ [\{P_B(u) + P_V(u)\}^T D^{-1}(u) P(u) + P(u)^T D(u)^{-1} \{P_B(u) + P_V(u)\} \right. \right. \\
&\quad \left. \left. - P(u)^T D^{-2}(u) \{D_B(u) + D_V(u)\} P(u)]^2 \right\} \right] + o(h^4 + \frac{1}{nh}) \\
&= \frac{1}{4} \mu_2^2 h^4 \text{trace} \left\{ 2P''(u) P''(u) P(u)^T P(u)^T D^{-2}(u) \right. \\
&\quad + 2P''(u)^T P''(u) \Sigma^{-1}(u) D^{-1}(u) + \Sigma^{-2}(u) D_{B1}^2(u) \\
&\quad + 2\Sigma^{-1}(u) P(u) P''(u) D^{-1}(u) D_{B1}(u) \Big\} \\
&\quad + \frac{\int K^2(y) dy}{nh f(u)} \text{trace} \left\{ P^*(u) \Sigma^{-1}(u) D^{-1}(u) + 2\Sigma^{-2}(u) \right\} + o(h^4 + \frac{1}{nh}),
\end{aligned}$$

we show the second equation of Theorem 3.

References

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