

Local Polynomial Modelling for Varying-Coefficient Informative Survival Models

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Supplementary Material

This note contains conditions and proofs for the asymptotic normality of the local log-likelihood estimator.

S1. Notation

Let $N_{1i}(s) = I(t_i \leq s, \delta_i = 1)$, $N_{2i}(s) = I(t_i \leq s, \delta_i = 0)$, $T_i(s) = I(t_i \geq s)$, and

$$\boldsymbol{\vartheta} = (\mathbf{a}_0^\top, \mathbf{a}_1^\top, \mathbf{a}_2^\top, \mathbf{b}_0^\top, \mathbf{b}_1^\top, \mathbf{b}_2^\top)^\top,$$

$$X_{i1}^* = (X_{i1}^\top, X_{i2}^\top, \mathbf{0}_{1 \times (p-p_1)}, X_{i1}^\top(U_i - u), X_{i2}^\top(U_i - u), \mathbf{0}_{1 \times (p-p_1)})^\top,$$

$$X_{i2}^* = (X_{i1}^\top, \mathbf{0}_{1 \times (p-p_1)}, X_{i2}^\top, X_{i1}^\top(U_i - u), \mathbf{0}_{1 \times (p-p_1)}, X_{i2}^\top(U_i - u))^\top.$$

The local log-likelihood function ℓ_2 can be expressed in terms of counting process as

$$\ell_3(\boldsymbol{\vartheta}, \tau) = \sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau K_h(U_i - u) \log \frac{g_l(\boldsymbol{\vartheta}^\top X_{il}^*)}{\sum_{j=1}^n T_j(v) g_l(\boldsymbol{\vartheta}^\top X_{jl}^*) K_h(U_j - u)} dN_{li}(v) \quad (\text{S1.1})$$

where we omitted D as it is independent of $\boldsymbol{\vartheta}$.

Let $(\Omega, \mathcal{F}, P(\boldsymbol{\eta}, h_{0,y}, h_{0,c}))$ be the sample space equipped with a right-continuous nondecreasing family of σ -algebras $(\mathcal{F}_s : s \in [0, \tau])$, where $\mathcal{F}_s = \sigma\{t_i \leq v, X_i, U_i, T_i(v), i =$

$1, 2, \dots, n, 0 \leq v \leq s$. All stochastic processes in this paper are assumed to be \mathcal{F}_s measurable. Define $M_{li}(s) = N_{li}(s) - \int_0^s \lambda_{li}(v)dv$, $l = 1, 2$, $i = 1, 2, \dots, n$, where λ_{li} is the intensity process of N_{li} . Obviously, $M_{li}(s)$ is a \mathcal{F}_s martingale and $M_{li}(s)$ are orthogonal with predictable variation process

$$\langle M_{li} \rangle (s) = \langle M_{li}, M_{li} \rangle (s) = \int_0^s \lambda_{li}(v)dv.$$

Let $\zeta = H(\vartheta - \xi)$, that is $\vartheta = H^{-1}\zeta + \xi$, then (S1.1) can be reparametrized to

$$\begin{aligned} \ell_4(\zeta, \tau) &= \ell_3(H^{-1}\zeta + \xi, \tau) \\ &= \sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau K_h(U_i - u) \log \frac{g_l(\zeta^\top W_{il}^* + \xi^\top X_{il}^*)}{\sum_{j=1}^n T_j(v) g_l(\zeta^\top W_{jl}^* + \xi^\top X_{jl}^*) K_h(U_j - u)} dN_{li}(v), \end{aligned} \quad (\text{S1.2})$$

where $W_{il}^* = H^{-1}X_{il}^*$.

For easy description, we write $h_1(v) = h_{0,y}(v)$, $h_2(v) = h_{0,c}(v)$, $Z_1^* = (X^\top, \mathbf{0}_{1 \times (p-p_1)})^\top$, $Z_2^* = (X_{01}^\top, \mathbf{0}_{1 \times (p-p_1)}, X_{02}^\top)^\top$, $Z_l(s) = (Z_l^{*\top}, Z_l^{*\top} s)^\top$, $X^{\otimes 0} = 1$, $X^{\otimes 1} = X$, $X^{\otimes 2} = XX^\top$. We use $\mathbf{0}$ without subscript to denote $\mathbf{0}_{2q \times 1}$, and $g_l^{(k)}(\cdot)$ to denote the k th derivative of $g_l(\cdot)$, $k = 0, 1, 2$, $l = 1, 2$. For any matrix A and vector \mathbf{a} , let $\|A\| = \sup_{i,j} |a_{ij}|$, $\|\mathbf{a}\| = \sup_i |a_i|$ and $|\mathbf{a}| = (\mathbf{a}^\top \mathbf{a})^{1/2}$. For $l = 1, 2$, $k = 0, 1, 2$, let

$$A_{nlk}(\zeta, v, u) = \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) T_i(v) g_l^{(k)}(\zeta^\top W_{il}^* + \xi^\top X_{il}^*) (W_{il}^*)^{\otimes k},$$

$$A_{nl0}^*(v, u) = \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) T_i(v) g_l(\theta_{0l}(U_i)^\top X_i),$$

$$a_{lk}(\zeta, v, u) = f(u) \int E \left[P(v, X, u) g_l^{(k)}(\zeta^\top Z_l(s) + \theta_{0l}(u)^\top X) Z_l(s)^{\otimes k} | U = u \right] K(s) ds,$$

$$\alpha_{lk}(v, u) = f(u) E \left[P(v, X, u) g_l^{(k)}(\theta_{0l}(u)^\top X) Z_l^{*\otimes k} | U = u \right],$$

$$\rho_l(v, u) = f(u) E \left\{ P(v, X, u) [g_l'(\theta_{0l}(u)^\top X)]^2 / g_l(\theta_{0l}(u)^\top X) Z_l^{*\otimes 2} | U = u \right\},$$

$$\rho_l(u) = \int_0^\tau \rho_l(v, u) h_l(v) dv, \quad \Gamma_l(u) = \rho_l(u) - \int_0^\tau \alpha_{l1}(v, u)^{\otimes 2} \alpha_{l0}(v, u)^{-1} h_l(v) dv.$$

S2. Condition

The following conditions are imposed to establish the asymptotic normality of the proposed estimator.

- (1) The kernel function $K(t)$ is a bounded and symmetric density function with compact support.
- (2) The functions $\beta_l(\cdot), l = 0, 1, 2, g_1(\cdot), g_2(\cdot)$ have continuous second derivatives around the point u and $g_1(\cdot), g_2(\cdot)$ are strictly positive.
- (3) The marginal density $f(\cdot)$ of U has a continuous derivative in some neighborhood of u , and $f(u) \neq 0$
- (4) $\int_0^\tau h_{0,y}(v)dv < \infty, \int_0^\tau h_{0,c}(v)dv < \infty$.
- (5) The conditional probability $P(v, x, u)$ is continuous with respect to u .
- (6) $n \rightarrow \infty, h \rightarrow 0, nh/\log n \rightarrow \infty, nh^5$ is bounded.
- (7) (Asymptotic regularity conditions) The matrix $\Delta(u)$ is positive definite at u , $\Omega(u)$ is nonsingular at u .
- (8) (Lindeberg condition)

$$(nh)^{-\frac{1}{2}} \sup_{l,i,s} \left| \frac{g_l'(\beta_0(U_i)^\top X_{i1} + \beta_l(U_i)^\top X_{i2})}{g_l(\beta_0(U_i)^\top X_{i1} + \beta_l(U_i)^\top X_{i2})} X_i \right| T_i(s) \xrightarrow{P} 0.$$

S3. Proof of asymptotic normality

We first present some useful lemmas.

Lemma S3.1. *Under conditions (1)-(6), we have*

$$A_{nlk}(\zeta, v, u) = a_{lk}(\zeta, v, u) + o_p(1), \quad A_{nl0}^*(v, u) = \alpha_{l0}(v, u) + o_p(1),$$

$l = 1, 2, k = 0, 1, 2$, where ζ lies in a neighborhood of $\mathbf{0}$ for fixed u .

This Lemma follows immediately from the same argument for Lemma A.1 in Fan, *et al.*, 2006.

Lemma S3.2. *Suppose the k -variate counting process \mathbf{N} has intensity process $\boldsymbol{\lambda}$. Let $M_i(s) = N(s) - \int_0^s \lambda(v)dv$, $i = 1, \dots, k$, $0 < s \leq \tau$, $\mathbf{M}(s) = (M_1(s), \dots, M_k(s))^T$, and $\mathbf{H}(s)$ be a $p \times k$ matrix of locally bounded and predictable. Then $\mathbf{M}(s)$ and $\int_0^s \mathbf{H}(v)d\mathbf{M}(v)$ are local square integrable martingales with*

$$\langle \mathbf{M} \rangle (s) = \left(\text{diag} \int_0^s \boldsymbol{\lambda}(v)dv \right), \quad \left\langle \int_0^s \mathbf{H}(v)d\mathbf{M}(v) \right\rangle (s) = \int_0^s \mathbf{H}(v) \left(\text{diag} \boldsymbol{\lambda}(v) \right) \mathbf{H}(v)^T dv,$$

where $\int_0^s \mathbf{H}(v)d\mathbf{M}(v)$ is the p dimensional vector whose j th component, $j = 1, \dots, p$, is the sum of integrals, with respect to the k components of $\mathbf{M}(v)$, of all entries on j th row of $\mathbf{H}(v)$.

See Andersen, *et al.*, 1993, Proposition II.4.1.

Lemma S3.3. (consistency of $\hat{\boldsymbol{\xi}}$) *Under conditions (1)-(7), we have*

$$H(\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}) \xrightarrow{P} \mathbf{0}.$$

Proof: By (S1.2), it follows that

$$\begin{aligned} & n^{-1} \ell_4(\zeta, s) - n^{-1} \ell_4(\mathbf{0}, s) \\ &= \frac{1}{n} \sum_{l=1}^2 \sum_{i=1}^n \int_0^s K_h(U_i - u) \left[\log \frac{g_l(\zeta^T W_{il}^* + \boldsymbol{\xi}^T X_{il}^*)}{g_l(\boldsymbol{\xi}^T X_{il}^*)} - \log \frac{A_{nl0}(\zeta, v, u)}{A_{nl0}(\mathbf{0}, v, u)} \right] dM_{li}(v) \\ & \quad + \sum_{l=1}^2 \left\{ \int_0^s B_{nl0}(\zeta, v, u) h_l(v) dv - \int_0^s \log \frac{A_{nl0}(\zeta, v, u)}{A_{nl0}(\mathbf{0}, v, u)} A_{nl0}^*(v, u) h_l(v) dv \right\} \\ & \equiv \sum_{l=1}^2 J_{nl}^{(1)}(\zeta, s) + \sum_{l=1}^2 J_{nl}^{(2)}(\zeta, s), \end{aligned}$$

where $B_{nl0}(\zeta, v, u) = \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) \log \frac{g_l(\zeta^T W_{il}^* + \xi^T X_{il}^*)}{g_l(\xi^T X_{il}^*)} T_i(v) g_l(\theta_{0l}(U_i)^T X_i) h_l(v) dv$. For each ζ , $J_{nl}^{(1)}(\zeta, s)$ is a local square integrable martingale with

$$\langle J_{nl}^{(1)}(\zeta, \cdot) \rangle (s) = n^{-2} \sum_{i=1}^n \int_0^s K_h^2(U_i - u) \left[\log \frac{g_l(\zeta^T W_{il}^* + \xi^T X_{il}^*)}{g_l(\xi^T X_{il}^*)} - \log \frac{A_{nl0}(\zeta, v, u)}{A_{nl0}(\mathbf{0}, v, u)} \right]^2 \lambda_{li}(v) dv.$$

By using the same argument as Lemma S3.1, it can be shown that $nh \langle J_{nl}^{(1)}(\zeta, \cdot) \rangle (\tau)$ converges in probability to some finite quantity (depending on ζ). By the inequality of Lengart, we have $J_{nl}^{(1)}(\zeta, s) = O_p((nh)^{-\frac{1}{2}})$, $0 \leq s \leq \tau$.

Using the same argument as that for Lemma S3.1, we obtain

$$\begin{aligned} J_{nl}^{(2)}(\zeta, s) &= \int_0^s b_{l0}(\zeta, v, u) h_l(v) dv - \int_0^s \log \frac{a_{l0}(\zeta, v, u)}{a_{l0}(\mathbf{0}, v, u)} \alpha_{l0}(v, u) h_l(v) dv + o_p(1) \\ &\equiv I_l(\zeta, s) + o_p(1), \end{aligned}$$

where $b_{l0}(\zeta, v, u) = f(u) \int E \left[P(v, X, u) \log \frac{g_l(\zeta^T Z_l(s) + \theta_{0l}(u)^T X)}{g_l(\theta_{0l}(u)^T X)} g_l(\theta_{0l}(u)^T X) | U = u \right] K(s) ds$.

Hence we have

$$n^{-1} \ell_4(\zeta, s) - n^{-1} \ell_4(\zeta, s) = I_1(\zeta, s) + I_2(\zeta, s) + o_p(1).$$

By simple calculation, we can see the first derivative of $(I_1(\zeta, s) + I_2(\zeta, s))$ is zero at $\zeta = \mathbf{0}$ and its second derivative is a negative definite matrix at $\zeta = \mathbf{0}$ by condition (7).

Finally we will show that the local log-likelihood function is concave. Since the second derivative of $J_{nl}^{(2)}(\zeta, s)$ with respect to ζ is

$$\begin{aligned} &\int_0^s \left\{ \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) T_i(v) \gamma_l(\zeta^T W_{il}^* + \xi^T X_{il}^*) W_{il}^{*\otimes 2} \left[g_l(\theta_{0l}(U_i)^T X_i) - g_l(\zeta^T W_{il}^* + \xi^T X_{il}^*) \right] \right. \\ &\quad \times A_{nl0}(\zeta, v, u) - \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) T_i(v) \gamma_l(\zeta^T W_{il}^* + \xi^T X_{il}^*) g_l(\zeta^T W_{il}^* + \xi^T X_{il}^*) W_{il}^{*\otimes 2} \\ &\quad \times \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) T_i(v) \left[g_l(\theta_{0l}(U_i)^T X_i) - g_l(\zeta^T W_{il}^* + \xi^T X_{il}^*) \right] \left. \right\} \frac{1}{A_{nl0}(\zeta, v, u)} \\ &\quad - \frac{1}{n} \sum_{i=1}^n K_h(U_i - u) T_i(v) g_l(\zeta^T W_{il}^* + \xi^T X_{il}^*) \left[\frac{g_l'(\zeta^T W_{il}^* + \xi^T X_{il}^*)}{g_l(\zeta^T W_{il}^* + \xi^T X_{il}^*)} W_{il}^* - \frac{A_{nl1}(\zeta, v, u)}{A_{nl0}(\zeta, v, u)} \right]^{\otimes 2} \\ &\quad \times \frac{A_{nl0}^*(v, u)}{A_{nl0}(\zeta, v, u)} h_l(v) dv, \end{aligned}$$

where $\gamma_l(\boldsymbol{\zeta}^\top W_{il}^* + \boldsymbol{\xi}^\top X_{il}^*)$ is the second derivative of $\log g_l(\boldsymbol{\zeta}^\top W_{il}^* + \boldsymbol{\xi}^\top X_{il}^*)$ with respect to $\boldsymbol{\zeta}$. Obviously, the last term is negatively semidefinite for any $\boldsymbol{\zeta}$ and with $\boldsymbol{\zeta}$ lies in a neighborhood of $\mathbf{0}$ for fixed u . Using the same argument as that for Lemma S3.1, we have that each component of the first two terms inside the bracket converges in probability to zero. Thus $J_{nl}^{(2)}(\boldsymbol{\zeta}, s)$ is negatively semidefinite matrix for any $\boldsymbol{\zeta}$. Therefore, $n^{-1}(\ell_4(\boldsymbol{\zeta}, \tau) - \ell_4(\mathbf{0}, \tau))$ is concave with maximiser being $\boldsymbol{\zeta} = \hat{\boldsymbol{\zeta}}$. Using the convex Theorem II.1 of Andersen & Gill (1982, Appendix II), we have $\hat{\boldsymbol{\zeta}}$ converges in probability to the maximiser of $(I_1(\boldsymbol{\zeta}, \tau) + I_2(\boldsymbol{\zeta}, \tau)) \mathbf{0}$.

Proof of Theorem: It is easy to see that

$$\begin{aligned} \tilde{\ell}_{n1}(\mathbf{0}, \tau) &= n^{-1} \frac{\partial \ell_4(\boldsymbol{\zeta}, \tau)}{\partial \boldsymbol{\zeta}} \Big|_{\boldsymbol{\zeta}=\mathbf{0}} \\ &= \frac{1}{n} \sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau K_h(U_i - u) \left[\frac{g'_l(\boldsymbol{\xi}^\top X_{il}^*)}{g_l(\boldsymbol{\xi}^\top X_{il}^*)} W_{il}^* - \frac{A_{nl1}(\mathbf{0}, v, u)}{A_{nl0}(\mathbf{0}, v, u)} \right] dM_{li}(v) \\ &\quad + \frac{1}{n} \sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau K_h(U_i - u) \left[\frac{g'_l(\boldsymbol{\xi}^\top X_{il}^*)}{g_l(\boldsymbol{\xi}^\top X_{il}^*)} W_{il}^* - \frac{A_{nl1}(\mathbf{0}, v, u)}{A_{nl0}(\mathbf{0}, v, u)} \right] T_i(v) g_l(\theta_{0l}(U_i)^\top X_i) h_l(v) dv \\ &\equiv \sum_{l=1}^2 R_{l1}(\mathbf{0}, \tau) + \sum_{l=1}^2 R_{l2}(\mathbf{0}, \tau). \end{aligned}$$

We first deal with $R_{l2}(\mathbf{0}, \tau)$. When U_i in the small neighborhood of u , by Taylor's expansion, it can be shown that

$$\begin{aligned} \sum_{l=1}^2 R_{l2}(\mathbf{0}, \tau) &= \frac{1}{2} h^2 \mu_2 \left\{ \begin{pmatrix} \Gamma_1(u) \\ \mathbf{0}_{q \times q} \end{pmatrix} \begin{pmatrix} \boldsymbol{\beta}_0''(u) \\ \boldsymbol{\beta}_1''(u) \\ \mathbf{0}_{(p-p_1) \times 1} \end{pmatrix} + \begin{pmatrix} \Gamma_2(u) \\ \mathbf{0}_{q \times q} \end{pmatrix} \begin{pmatrix} \boldsymbol{\beta}_0''(u) \\ \mathbf{0}_{(p-p_1) \times 1} \\ \boldsymbol{\beta}_2''(u) \end{pmatrix} \right\} (1 + o_p(1)) \\ &\equiv r_n(u) (1 + o_p(1)). \end{aligned}$$

Define $R_l^*(s) = \sqrt{nh} R_{l1}(\mathbf{0}, s)$, $l = 1, 2$. Using same argument as that for Lemmas S3.1 and S3.2, we have that

$$\langle (R_1^* + R_2^*) \rangle (\tau) \xrightarrow{P} \begin{pmatrix} (\Gamma_1(u) + \Gamma_2(u))\nu_0 & \mathbf{0}_{q \times q} \\ \mathbf{0}_{q \times q} & (\rho_1(u) + \rho_2(u))\nu_2 \end{pmatrix} \equiv \Sigma_1(u).$$

It remains to be proved that for all $\epsilon > 0$,

$$\sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau \{S_{lij}(v)\}^2 \lambda_{li}(v) I(|S_{lij}(v)| > \epsilon) dv \xrightarrow{P} 0,$$

where $S_{lij}(v) = \sqrt{\frac{h}{n}} K_h(U_i - u) \left[\frac{g'_l(\boldsymbol{\xi}^\top X_{il}^*)}{g_l(\boldsymbol{\xi}^\top X_{il}^*)} W_{il}^* - \frac{A_{nl1}(\mathbf{0}, v, u)}{A_{nl0}(\mathbf{0}, v, u)} \right]_j$, $j = 1, 2, \dots, 2q$.

By using the elementary inequality

$$|\mathbf{a} - \mathbf{b}|^2 I(|\mathbf{a} - \mathbf{b}| > \epsilon) \leq 4|\mathbf{a}|^2 I(|\mathbf{a}| > \frac{\epsilon}{2}) + 4|\mathbf{b}|^2 I(|\mathbf{b}| > \frac{\epsilon}{2})$$

and Taylor's expansion of $\beta_j(U_i)$, $j = 0, 1, 2$, at u and the continuity of $g_l(\cdot), g'_l(\cdot)$, $l = 1, 2$, together with condition (8), we obtain the above result.

Appealing Rebolledos's martingale central limit theorem, we have

$$\sqrt{nh}(\tilde{\ell}_{n1}(\mathbf{0}, \tau) - r_n(u)) \xrightarrow{D} \mathbf{N}(\mathbf{0}, \Sigma_1(u)). \quad (\text{S3.1})$$

We are now going to show that $\tilde{\ell}_{n2}(\boldsymbol{\zeta}^*, \tau) = \frac{1}{n} \frac{\partial^2 \ell_4(\boldsymbol{\zeta}, \tau)}{\partial \boldsymbol{\zeta} \partial \boldsymbol{\zeta}^\top} \Big|_{\boldsymbol{\zeta}=\boldsymbol{\zeta}^*}$ converges in probability to a finite constant matrix for any random $\boldsymbol{\zeta}^*$ between $\mathbf{0}$ and $\hat{\boldsymbol{\zeta}}$. Since $\boldsymbol{\zeta}^* \xrightarrow{P} \mathbf{0}$, by the mean-value theorem we have that

$$\tilde{\ell}_{n2}(\boldsymbol{\zeta}^*, \tau) = \tilde{\ell}_{n2}(\mathbf{0}, \tau) + o_p(1),$$

and

$$\begin{aligned} \tilde{\ell}_{n2}(\mathbf{0}, \tau) &= \frac{1}{n} \sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau K_h(U_i - u) \left[\frac{g''_l(\boldsymbol{\xi}^\top X_{il}^*) g_l(\boldsymbol{\xi}^\top X_{il}^*) - [g'_l(\boldsymbol{\xi}^\top X_{il}^*)]^2}{g_l^2(\boldsymbol{\xi}^\top X_{il}^*)} W_{il}^{*\otimes 2} \right] dM_{li}(v) \\ &\quad - \frac{1}{n} \sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau K_h(U_i - u) \frac{A_{nl2}(\mathbf{0}, v, u) A_{nl0}(\mathbf{0}, v, u) - A_{nl1}(\mathbf{0}, v, u)^{\otimes 2}}{A_{nl0}^2(\mathbf{0}, v, u)} dM_{li}(v) \\ &\quad + \frac{1}{n} \sum_{l=1}^2 \sum_{i=1}^n \int_0^\tau K_h(U_i - u) \left[\frac{g''_l(\boldsymbol{\xi}^\top X_{il}^*) g_l(\boldsymbol{\xi}^\top X_{il}^*) - [g'_l(\boldsymbol{\xi}^\top X_{il}^*)]^2}{g_l^2(\boldsymbol{\xi}^\top X_{il}^*)} W_{il}^{*\otimes 2} \right. \\ &\quad \left. - \frac{A_{nl2}(\mathbf{0}, v, u) A_{nl0}(\mathbf{0}, v, u) - A_{nl1}(\mathbf{0}, v, u)^{\otimes 2}}{A_{nl0}^2(\mathbf{0}, v, u)} \right] \lambda_{li}(v) dv. \end{aligned}$$

Similar to the proof of $J_{nl}^{(1)}(\boldsymbol{\zeta}, s)$ in Lemma S3.3, it can be shown that each component in the first and second terms equal $O_p((nh)^{-\frac{1}{2}})$. By simple calculation, we can see the third term

converges in probability to

$$- \begin{pmatrix} \Gamma_1(u) + \Gamma_2(u) & \mathbf{0}_{q \times q} \\ \mathbf{0}_{q \times q} & (\rho_1(u) + \rho_2(u))\mu_2 \end{pmatrix} \equiv -\Sigma_2(u).$$

Hence $\tilde{\ell}_{n2}(\zeta^*, \tau) \xrightarrow{P} -\Sigma_2(u)$.

As $\hat{\zeta}$ maximizes $n^{-1}\ell_4(\zeta, \tau)$ and $\hat{\zeta} \xrightarrow{P} \mathbf{0}$, by Taylor's expansion at $\mathbf{0}$ and the above result,

we have

$$\hat{\zeta} - \Sigma_2(u)^{-1}r_n(u) = - \left(\tilde{\ell}_{n2}(\zeta^*, \tau) \right)^{-1} \left(\tilde{\ell}_{n1}(\mathbf{0}, \tau) - r_n(u) \right) + o_p(1).$$

This together with (S3.1) lead to

$$\sqrt{nh} \left(\hat{\zeta} - \Sigma_2(u)^{-1}r_n(u) \right) \xrightarrow{D} \mathbf{N} \left(\mathbf{0}, \Sigma_2(u)^{-1}\Sigma_1(u)\Sigma_2(u)^{-1} \right).$$

By simple and straightforward calculation, it follows that

$$r_n(u) = \frac{1}{2}h^2\mu_2 \begin{pmatrix} \Delta(u) \\ \mathbf{0}_{q \times q} \end{pmatrix} \boldsymbol{\eta}''(u), \quad \Sigma_2(u)^{-1}r_n(u) = \frac{1}{2}h^2\mu_2 \mathbf{e}_{2q \times q} \boldsymbol{\eta}''(u),$$

and

$$\Sigma_2(u)^{-1}\Sigma_1(u)\Sigma_2(u)^{-1} = \begin{pmatrix} \Delta(u)^{-1}\nu_0 & \mathbf{0}_{q \times q} \\ \mathbf{0}_{q \times q} & \Omega(u)^{-1}\mu_2^{-2}\nu_2 \end{pmatrix}.$$