## SUPPLEMENTAL MATERIAL TO "MODEL SELECTION AND STRUCTURE SPECIFICATION IN ULTRA-HIGH DIMENSIONAL GENERALISED SEMI-VARYING COEFFICIENT MODELS"

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In this supplemental material, we provide the detailed proofs of the main results stated in Section 3 of the main document as well as some technical lemmas which are useful in our proofs.

## APPENDIX B: PROOFS OF THE MAIN RESULTS

In this appendix, we give the detailed proofs of the main theoretical results developed in Section 3.

Proof of Proposition 3.1 (i). Recall that

$$\widetilde{\mathbf{a}}_k = \left[ \widetilde{a}_1(U_k), \cdots, \widetilde{a}_{d_n}(U_k) \right]^{\mathrm{T}}, \quad \widetilde{\mathbf{b}}_k = \left[ \widetilde{a}_1(U_k), \cdots, \widetilde{a}_{d_n}(U_k) \right]^{\mathrm{T}}.$$

The basic idea used in the proof of this proposition is similar to that in Bickel  $et\ al\ (2009)$  and Lian (2012). However, as the kernel-based smoothing method is used, we need to derive the uniform convergence rates for the kernel-based quantities, which makes the technical argument more complicated than that in Bickel  $et\ al\ (2009)$  and Lian (2012).

We start with the proof that with probability approaching one, uniformly for  $k = 1, \dots, n$ ,

$$(\mathrm{B.1}) \qquad \max\Big\{\sum_{j=s_{n2}+1}^{d_n}|d_{jk}|,\; \sum_{j=s_{n1}+1}^{d_n}|\dot{d}_{jk}|\Big\} \leq b\Big(\sum_{j=1}^{s_{n2}}|d_{jk}| + \sum_{j=1}^{s_{n1}}|\dot{d}_{jk}|\Big),$$

where  $b = \max\{\lambda_1/\lambda_2, \lambda_2/\lambda_1\} + \delta$  for any small  $\delta > 0$ , where

$$d_{jk} = \widetilde{a}_j(U_k) - a_j(U_k)$$
 and  $\dot{d}_{jk} = h \left[ \widetilde{a}_j(U_k) - \dot{a}_j(U_k) \right]$ 

for 
$$j = 1, \dots, d_n$$
 and  $k = 1, \dots, n$ .

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By the definitions of  $\widetilde{\mathbf{a}}_k$  and  $\widetilde{\mathbf{b}}_k$ , we readily have

(B.2) 
$$Q_{nk}(\widetilde{\mathbf{a}}_k, \widetilde{\mathbf{b}}_k) \ge Q_{nk}(\mathbf{a}_{k0}, \mathbf{b}_{k0}),$$

where  $\mathbf{a}_{k0}$  and  $\mathbf{b}_{k0}$  are defined in Section 2 of the main document. From (B.2), we have

(B.3) 
$$\mathcal{L}_{nk}(\widetilde{\mathbf{a}}_k, \widetilde{\mathbf{b}}_k) - \mathcal{L}_{nk}(\mathbf{a}_{k0}, \mathbf{b}_{k0})$$

$$\geq \lambda_1 \Big[ \sum_{j=1}^{d_n} |\widetilde{a}_j(U_k)| - \sum_{j=1}^{d_n} |a_j(U_k)| \Big] + \lambda_2 \Big[ \sum_{j=1}^{d_n} |\widetilde{a}_j(U_k)| - \sum_{j=1}^{d_n} |\dot{a}_j(U_k)| \Big].$$

By the concavity condition of  $\ell(\cdot,\cdot)$  (c.f., Assumption 2(ii)), we may show that

(B.4) 
$$\mathcal{L}_{nk}(\widetilde{\mathbf{a}}_k, \widetilde{\mathbf{b}}_k) - \mathcal{L}_{nk}(\mathbf{a}_{k0}, \mathbf{b}_{k0}) \leq \mathbf{d}_k^{\mathrm{T}} \dot{\mathcal{L}}_{nk},$$

where

$$\dot{\mathcal{L}}_{nk} = \frac{1}{n} \sum_{i=1}^{n} q_1 \left[ \sum_{j=1}^{d_n} a_j(U_k) + \dot{a}_j(U_k)(U_i - U_k) x_{ij}, y_i \right] \begin{pmatrix} X_i \\ \frac{U_i - U_k}{h} \cdot X_i \end{pmatrix} \cdot K_h(U_i - U_k)$$

and  $\mathbf{d}_k = (d_{1k}, \dots, d_{d_nk}, \dot{d}_{1k}, \dots, \dot{d}_{d_nk})^{\mathrm{T}}$ . By Lemma C.1 which is given in Appendix C, we may show that

(B.5) 
$$\max_{1 \le j \le d_n} \sup_{1 \le k \le n} \left| \frac{1}{n} \sum_{i=1}^n q_1 \left[ \sum_{j_1=1}^{d_n} a_{j_1}(U_i) x_{ij_1}, y_i \right] x_{ij} K_h(U_i - U_k) \right|$$
$$= O_P\left( \sqrt{\frac{\log h^{-1}}{nh}} \right)$$

and

(B.6)
$$\max_{1 \le j \le d_n} \sup_{1 \le k \le n} \left| \frac{1}{n} \sum_{i=1}^n q_1 \left[ \sum_{j_1=1}^{d_n} a_{j_1}(U_i) x_{ij_1}, y_i \right] x_{ij} \left( \frac{U_i - U_k}{h} \right) K_h(U_i - U_k) \right|$$

$$= O_P\left( \sqrt{\frac{\log h^{-1}}{nh}} \right).$$

Then, by (B.5), (B.6), the standard calculation in kernel-based smoothing and the argument in the proof of Lemma C.1, we may show that

(B.7) 
$$\mathbf{d}_{k}^{\mathrm{T}} \dot{\mathcal{L}}_{nk} \leq O_{P} \left( \sqrt{\frac{\log h^{-1}}{nh}} + s_{n2} h^{2} \right) \cdot \left( \sum_{j=1}^{d_{n}} |d_{jk}| + \sum_{j=1}^{d_{n}} |\dot{d}_{jk}| \right)$$

uniformly for  $k = 1, \dots, n$ .

On the other hand, by the triangle inequality, we may prove that

(B.8) 
$$\lambda_{1} \left[ \sum_{j=1}^{d_{n}} |\widetilde{a}_{j}(U_{k})| - \sum_{j=1}^{d_{n}} |a_{j}(U_{k})| \right]$$

$$= \lambda_{1} \sum_{j=1}^{s_{n2}} \left( |\widetilde{a}_{j}(U_{k})| - |a_{j}(U_{k})| \right) + \lambda_{1} \sum_{j=s_{n2}+1}^{d_{n}} |\widetilde{a}_{j}(U_{k})|$$

$$\geq -\lambda_{1} \sum_{j=1}^{s_{n2}} |d_{jk}| + \lambda_{1} \sum_{j=s_{n2}+1}^{d_{n}} |d_{jk}|.$$

Similarly, we also have

(B.9) 
$$\lambda_2 \left[ \sum_{i=1}^{d_n} |\widetilde{a}_j(U_k)| - \sum_{i=1}^{d_n} |\dot{a}_j(U_k)| \right] \ge -\lambda_2 \sum_{i=1}^{s_{n1}} |\dot{d}_{jk}| + \lambda_2 \sum_{i=s_{n1}+1}^{d_n} |\dot{d}_{jk}|.$$

By (B.3), (B.4), (B.7)–(B.9) and the condition that  $\sqrt{\frac{\log h^{-1}}{nh}} + s_{n2}h^2 = o(\lambda_1 + \lambda_2)$  and  $\lambda_1 \propto \lambda_2$  (c.f., Assumption 5), we can complete the proof of (B.1).

Let

$$\mathbf{u}_1 = (u_{11}, \cdots, u_{1d_n})^{\mathrm{T}}$$
 and  $\mathbf{u}_2 = (u_{21}, \cdots, u_{2d_n})^{\mathrm{T}}$ 

be two  $d_n$ -dimensional column vectors and define

$$\Omega(C_0) = \left\{ \left( \mathbf{u}_1^{\mathrm{T}}, \mathbf{u}_2^{\mathrm{T}} \right)^{\mathrm{T}} : \|\mathbf{u}_1\|^2 = \|\mathbf{u}_2\|^2 = C_0, \\
\sum_{j=1}^{d_n} \left( |u_{1j}| + |u_{2j}| \right) \le 2(1+b) \sum_{j=1}^{s_{n2}} \left( |u_{1j}| + |u_{2j}| \right) \right\},$$

where  $C_0$  is a positive constant which could be sufficiently large. By the concavity of  $\ell(\cdot, \cdot)$ , we only need to prove that there exists a local maximiser  $(\tilde{\mathbf{a}}_k, h\tilde{\mathbf{b}}_k)$  in the interior of  $\{(\mathbf{a}_{k0} + \gamma_n \mathbf{u}_1, h\mathbf{b}_{k0} + \gamma_n \mathbf{u}_2) : (\mathbf{u}_1^T, \mathbf{u}_2^T)^T \in \mathbf{\Omega}(C_0)\}$ , where  $\gamma_n = \sqrt{s_{n2}}\lambda_1$ .

Observe that

(B.10) 
$$\mathcal{Q}_{nk}\left[\mathbf{a}_{k0} + \gamma_n \mathbf{u}_1, \mathbf{b}_{k0} + \gamma_n \mathbf{u}_2/h\right] - \mathcal{Q}_{nk}\left(\mathbf{a}_{k0}, \mathbf{b}_{k0}\right) = \sum_{l=1}^{3} \mathcal{I}_{nk}(l),$$

where

$$\mathcal{I}_{nk}(1) = \mathcal{L}_{nk}(\mathbf{a}_{k0} + \gamma_n \mathbf{u}_1, \mathbf{b}_{k0} + \gamma_n \mathbf{u}_2/h) - \mathcal{L}_{nk}(\mathbf{a}_{k0}, \mathbf{b}_{k0}), 
\mathcal{I}_{nk}(2) = -\lambda_1 \Big( \sum_{j=1}^{d_n} |a_j(U_k) + \gamma_n u_{1j}| - \sum_{j=1}^{d_n} |a_j(U_k)| \Big), 
\mathcal{I}_{nk}(3) = -\lambda_2 \Big( \sum_{j=1}^{d_n} |h\dot{a}_j(U_k) + \gamma_n u_{2j}| - \sum_{j=1}^{d_n} |h\dot{a}_j(U_k)| \Big).$$

We first consider  $\mathcal{I}_{nk}(1)$ . Letting  $\mathbf{u} = (\mathbf{u}_1^{\mathrm{T}}, \mathbf{u}_2^{\mathrm{T}})^{\mathrm{T}}$  and by the definition of  $\mathcal{L}_{nk}(\cdot,\cdot)$  in Section 2, we have

(B.11) 
$$\mathcal{I}_{nk}(1) \stackrel{P}{\sim} \gamma_n \mathbf{u}^{\mathrm{T}} \dot{\mathcal{L}}_{nk} + \frac{1}{2} \gamma_n^2 \mathbf{u}^{\mathrm{T}} \ddot{\mathcal{L}}_{nk}(\mathbf{a}_k^*, \mathbf{b}_k^*) \mathbf{u},$$

where  $a_n \stackrel{P}{\sim} b_n$  denotes that  $a_n = b_n(1 + o_P(1))$ ,  $(\mathbf{a}_k^*, \mathbf{b}_k^*)$  lies between  $(\mathbf{a}_{k0} + \gamma_n \mathbf{u}_1, \mathbf{b}_{k0} + \gamma_n \mathbf{u}_2/h)$  and  $(\mathbf{a}_{k0}, \mathbf{b}_{k0})$ ,

$$\ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k) = \begin{bmatrix} \ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k, 0) & \ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k, 1) \\ \ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k, 1) & \ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k, 2) \end{bmatrix}$$

with

$$\ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k, l) = \frac{1}{n} \sum_{i=1}^n q_2 \left\{ \sum_{j=1}^{d_n} \left[ \alpha_{jk} + \beta_{jk} (U_i - U_k) \right] x_{ij}, y_i \right\} \left( \frac{U_i - U_k}{h} \right)^l \cdot X_i X_i^{\mathrm{T}} K_h(U_i - U_k)$$

for l = 0, 1, 2, where  $\mathbf{a}_k = (\alpha_{1k}, \dots, \alpha_{d_n k})^{\mathrm{T}}$  and  $\mathbf{b}_k = (\beta_{1k}, \dots, \beta_{d_n k})^{\mathrm{T}}$ . Note that for  $\mathbf{u} \in \mathbf{\Omega}(C_0)$ ,

(B.12) 
$$\sum_{j=1}^{d_n} (|u_{1j}| + |u_{2j}|) \le 2(1+b) \sum_{j=1}^{s_{n2}} (|u_{1j}| + |u_{2j}|).$$

Using Lemma C.1 in Appendix C, the Cauchy-Schwarz inequality and (B.12), we can show that uniformly for  $k = 1, \dots, n$ ,

(B.13) 
$$\gamma_n \mathbf{u}^{\mathrm{T}} \dot{\mathcal{L}}_{nk} = o_P(\gamma_n^2) \cdot \|\mathbf{u}\|.$$

On the other hand, note that

(B.14) 
$$\frac{1}{2}\gamma_n^2 \mathbf{u}^{\mathrm{T}} \ddot{\mathcal{L}}_{nk}(\mathbf{a}_k^*, \mathbf{b}_k^*) \mathbf{u}$$
$$= \frac{1}{2}\gamma_n^2 \mathbf{u}^{\mathrm{T}} \left[ \ddot{\mathcal{L}}_{nk}(\mathbf{a}_k^*, \mathbf{b}_k^*) - \ddot{\mathcal{L}}_n(U_k) \right] \mathbf{u} + \frac{1}{2}\gamma_n^2 \mathbf{u}^{\mathrm{T}} \ddot{\mathcal{L}}_n(U_k) \mathbf{u},$$

where  $\ddot{\mathcal{L}}_n(U_k)$  is defined at the beginning of Appendix A. By Assumption 2(iii), we readily have

(B.15) 
$$\frac{1}{2}\gamma_n^2 \mathbf{u}^{\mathrm{T}} \ddot{\mathcal{L}}_n(U_k) \mathbf{u} \le -\frac{1}{2}\rho_1 \gamma_n^2 ||\mathbf{u}||^2 < 0$$

uniformly for  $k=1,\dots,n$ . By (B.12), Assumptions 2(ii), the condition  $s_{n2}^2\lambda_1=o(1)$  in Assumption 5 and following the proof of Lemma C.1, we may prove that uniformly for  $k=1,\dots,n$ ,

(B.16) 
$$\gamma_n^2 \mathbf{u}^{\mathrm{T}} \left[ \ddot{\mathcal{L}}_{nk} (\mathbf{a}_k^*, \mathbf{b}_k^*) - \ddot{\mathcal{L}}_n(U_k) \right] \mathbf{u}$$

$$= O_P \left( \gamma_n^3 \left[ \sum_{j=1}^{d_n} (|u_{1j}| + |u_{2j}|) \right]^3 \right) = O_P \left( \gamma_n^3 \left[ \sum_{j=1}^{s_{n2}} (|u_{1j}| + |u_{2j}|) \right]^3 \right)$$

$$= O_P \left( \gamma_n^3 s_{n2}^{3/2} ||\mathbf{u}||^3 \right) = o_P (\gamma_n^2) \cdot \left( ||\mathbf{u}||^2 \right).$$

Hence, by (B.11) and (B.13)–(B.16), when n is sufficiently large and  $C_0$  is large enough, we have

(B.17) 
$$\mathcal{I}_{nk}(1) \stackrel{P}{\sim} \frac{1}{2} \gamma_n^2 \mathbf{u}^{\mathrm{T}} \ddot{\mathcal{L}}_{nk}(U_k) \mathbf{u}.$$

We next consider  $\mathcal{I}_{nk}(2)$  and  $\mathcal{I}_{nk}(3)$ . It is easy to show that

(B.18) 
$$\mathcal{I}_{nk}(2) = -\lambda_1 \Big[ \sum_{j=1}^{d_n} |a_j(U_k) + \gamma_n u_{1j}| - \sum_{j=1}^{d_n} |a_j(U_k)| \Big]$$
  

$$\leq \lambda_1 \sum_{j=1}^{s_{n2}} \Big[ |a_j(U_k)| - |a_j(U_k) + \gamma_n u_{1j}| \Big] - \lambda_1 \sum_{j=s_{n2}+1}^{d_n} |\gamma_n u_{1j}|$$

$$= O_P(\gamma_n^2) \cdot \|\mathbf{u}_1\| - \lambda_1 \sum_{j=s_{n2}+1}^{d_n} |\gamma_n u_{1j}|.$$

Similarly, noting that  $\lambda_1 \propto \lambda_2$  we also have

(B.19) 
$$\mathcal{I}_{nk}(3) = O_P(\gamma_n^2) \cdot ||\mathbf{u}_2|| - \lambda_2 \sum_{j=s_{n,1}+1}^{d_n} |\gamma_n u_{2j}|.$$

Hence, by (B.10) and (B.17)–(B.19), we can prove that the leading term of  $\mathcal{I}_{nk}(1) + \mathcal{I}_{nk}(2) + \mathcal{I}_{nk}(3)$  is negative in probability uniformly in k by choosing sufficiently large  $C_0$ . Hence, we may find a local maximiser  $(\tilde{\mathbf{a}}_k, h\tilde{\mathbf{b}}_k)$  in the interior of  $\{(\mathbf{a}_{k0} + \gamma_n \mathbf{u}_1, h\mathbf{b}_{k0} + \gamma_n \mathbf{u}_2) : (\mathbf{u}_1^T, \mathbf{u}_2^T)^T \in \mathbf{\Omega}(C_0)\}$ , which completes the proof of Proposition 3.1(i).

**Proof of Proposition 3.1 (ii)**. The proof is similar to that in the proof of Proposition 3.1(i) with the role of Lemma C.1 replaced by Lemma C.2 (given in Appendix C). □

**Proof of Theorem 3.1.** We start with the proof of the convergence rates for the biased oracle estimators  $\overline{\mathcal{A}}_n^{bo}$  and  $\overline{\mathcal{B}}_n^{bo}$ . According to the definition, we have

(B.20) 
$$(\overline{\mathcal{A}}_n^{bo}, \overline{\mathcal{B}}_n^{bo}) = \arg \max \mathcal{Q}_n^2(\mathcal{A}^o, \mathcal{B}^o),$$

where  $\mathcal{A}^o$  and  $\mathcal{B}^o$  are defined as in Section 3. Recall that  $\mathcal{A}_0$  and  $\mathcal{B}_0$  are the vectors of the true functional coefficients and their derivative functions, and denote

$$\mathcal{U}_1 = \begin{bmatrix} \mathbf{u}_1^{\mathrm{T}}(1), \cdots, \mathbf{u}_1^{\mathrm{T}}(n) \end{bmatrix}^{\mathrm{T}}, \quad \mathcal{U}_2 = \begin{bmatrix} \mathbf{u}_2^{\mathrm{T}}(1), \cdots, \mathbf{u}_2^{\mathrm{T}}(n) \end{bmatrix}^{\mathrm{T}},$$

where both  $\mathbf{u}_1(k)$  and  $\mathbf{u}_2(k)$  are  $d_n$ -dimensional column vectors,  $k = 1, \dots, n$ , the last  $d_n - s_{n2}$  elements of  $\mathbf{u}_1(k)$  and the last  $d_n - s_{n1}$  elements of  $\mathbf{u}_2(k)$  are zeroes. Define

$$\Omega_n^*(C_*) = \{ (\mathcal{U}_1^{\mathrm{T}}, \ \mathcal{U}_2^{\mathrm{T}})^{\mathrm{T}} : \|\mathcal{U}_1\|^2 = \|\mathcal{U}_2\|^2 = nC_* \},$$

where  $C_*$  is a positive constant which can be sufficiently large.

For 
$$(\mathcal{U}_1^{\Gamma}, \ \mathcal{U}_2^{\Gamma})^{\Gamma} \in \mathbf{\Omega}_n^*(C_*)$$
, observe that

(B.21) 
$$Q_n^2 (A_0 + \gamma_n^* \mathcal{U}_1, \mathcal{B}_0 + \gamma_n^* \mathcal{U}_2/h) - Q_n^2 (A_0, \mathcal{B}_0) = \mathcal{I}_n(1) + \mathcal{I}_n(2) + \mathcal{I}_n(3),$$

where 
$$\gamma_n^* = \sqrt{s_{n2}/nh}$$
,

$$\mathcal{I}_n(1) = \mathcal{L}_n^{\diamond} \left( \mathcal{A}_0 + \gamma_n^* \mathcal{U}_1, \mathcal{B}_0 + \gamma_n^* \mathcal{U}_2 / h \right) - \mathcal{L}_n^{\diamond} (\mathcal{A}_0, \mathcal{B}_0),$$

$$\mathcal{I}_{n}(2) = \sum_{j=1}^{d_{n}} \dot{p}_{\lambda_{4}}(\|\widetilde{\boldsymbol{\alpha}}_{j}\|)\|\boldsymbol{\alpha}_{j0}\| - \sum_{j=1}^{d_{n}} \dot{p}_{\lambda_{4}}(\|\widetilde{\boldsymbol{\alpha}}_{j}\|)\|\boldsymbol{\alpha}_{j0} + \gamma_{n}^{*}\mathbf{u}_{1j}\|,$$

$$\mathcal{I}_{n}(3) = \sum_{j=1}^{d_{n}} \dot{p}_{\lambda_{4}^{*}}(\widetilde{D}_{j}) \|h\beta_{j0}\| - \sum_{j=1}^{d_{n}} \dot{p}_{\lambda_{4}^{*}}(\widetilde{D}_{j}) \|h\beta_{j0} + \gamma_{n}^{*}\mathbf{u}_{2j}\|,$$

in which  $\boldsymbol{\alpha}_{j0} = \begin{bmatrix} a_j(U_1), \cdots, a_j(U_n) \end{bmatrix}^T$ ,  $\boldsymbol{\beta}_{j0} = \begin{bmatrix} \dot{a}_j(U_1), \cdots, \dot{a}_j(U_n) \end{bmatrix}^T$ ,  $\mathbf{u}_{1j} = \begin{bmatrix} u_{1j}(1), \cdots, u_{1j}(n) \end{bmatrix}^T$ ,  $\mathbf{u}_{2j} = \begin{bmatrix} u_{2j}(1), \cdots, u_{2j}(n) \end{bmatrix}^T$ ,  $u_{1j}(k)$  and  $u_{2j}(k)$  are the j-th component of vectors  $\mathbf{u}_1(k)$  and  $\mathbf{u}_2(k)$ , respectively.

For  $\mathcal{I}_n(1)$ , by the definition of  $\mathcal{L}_n^{\diamond}(\cdot,\cdot)$  in Section 2, we have

(B.22) 
$$\mathcal{I}_n(1) = \mathcal{I}_n(4) + \mathcal{I}_n(5) + o_P((\gamma_n^*)^2) \cdot (\|\mathcal{U}_1\|^2 + \|\mathcal{U}_2\|^2),$$

where

$$\mathcal{I}_{n}(4) = \gamma_{n}^{*} \mathcal{V}_{n}^{\Gamma}(\mathcal{U}_{1}, \mathcal{U}_{2}) \dot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0}), 
\mathcal{I}_{n}(5) = \frac{1}{2} (\gamma_{n}^{*})^{2} \mathcal{V}_{n}^{\Gamma}(\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \mathcal{V}_{n}(\mathcal{U}_{1}, \mathcal{U}_{2}).$$

The detailed proof of (B.22) will be provided in Appendix C below. By some elementary but tedious calculations, we can show that

(B.23) 
$$\mathcal{I}_n(4) = O_P((\gamma_n^*)^2 n^{1/2}) \cdot (\|\mathcal{U}\| + \|\mathcal{V}\|).$$

The detailed proof of (B.23) will be also given in Appendix C below. For  $\mathcal{I}_n(5)$ , note that

$$\mathcal{I}_{n}(5) = \frac{1}{2} (\gamma_{n}^{*})^{2} \mathcal{V}_{n}^{\Gamma}(\mathcal{U}_{1}, \mathcal{U}_{2}) \Big[ \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) - \ddot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0}) \Big] \mathcal{V}_{n}(\mathcal{U}_{1}, \mathcal{U}_{2}) + \frac{1}{2} (\gamma_{n}^{*})^{2} \mathcal{V}_{n}^{\Gamma}(\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0}) \mathcal{V}_{n}(\mathcal{U}_{1}, \mathcal{U}_{2})$$
(B.24) 
$$\equiv \mathcal{I}_{n}(6) + \mathcal{I}_{n}(7).$$

By Assumption 2(iii) and the definitions of  $\mathcal{U}_1$  and  $\mathcal{U}_2$ , we may show that

(B.25) 
$$\mathcal{I}_n(7) \le -\frac{1}{2}\rho_1(\gamma_n^*)^2 (\|\mathcal{U}_1\|^2 + \|\mathcal{U}_2\|^2) < 0.$$

By Assumption 2(ii) and using Proposition 3.1, we can prove that

(B.26) 
$$\mathcal{I}_n(6) = o_P((\gamma_n^*)^2) \cdot (\|\mathcal{U}_1\|^2 + \|\mathcal{U}_2\|^2),$$

which, together with (B.22)–(B.25), implies that  $\mathcal{I}_n(7)$  is the leading term of  $\mathcal{I}_n(1)$ . Hence, when n is sufficiently large, by taking  $C_*$  large enough, we have

(B.27) 
$$\mathcal{I}_n(1) \stackrel{P}{\sim} \frac{1}{2} (\gamma_n^*)^2 \mathcal{V}_n^{\Gamma}(\mathcal{U}_1, \mathcal{U}_2) \ddot{\mathcal{L}}_n(\mathcal{A}_0, \mathcal{B}_0) \mathcal{V}_n(\mathcal{U}_1, \mathcal{U}_2).$$

We next consider  $\mathcal{I}_n(2)$ . Noting that  $\mathbf{u}_{1j} = \mathbf{0}$  for  $j = s_{n2+1}, \dots, d_n$ , we have

$$\mathcal{I}_{n}(2) = \sum_{j=1}^{d_{n}} \dot{p}_{\lambda_{4}}(\|\widetilde{\alpha}_{j}\|) \|\alpha_{j0}\| - \sum_{j=1}^{d_{n}} \dot{p}_{\lambda_{4}}(\|\widetilde{\alpha}_{j}\|) \|\alpha_{j0} + \gamma_{n}^{*} \mathbf{u}_{1j}\| \\
= \sum_{j=1}^{s_{n2}} \dot{p}_{\lambda_{4}}(\|\widetilde{\alpha}_{j}\|) (\|\alpha_{j0}\| - \|\alpha_{j0} + \gamma_{n}^{*} \mathbf{u}_{1j}\|).$$

By Proposition 3.1 and (A.4) in Assumption 6, we may show that with probability approaching one,

$$\min_{1 \le j \le s_{n2}} \|\widetilde{\boldsymbol{\alpha}}_j\| > \frac{1}{2} b_{\diamond} n^{1/2},$$

which together with the condition of  $\lambda_4 = o(n^{1/2})$  and the SCAD structure, implies that

(B.28) 
$$\mathcal{I}_n(2) = o_P((\gamma_n^*)^2) \cdot ||\mathcal{U}_1||^2.$$

Similarly, we may also show that

(B.29) 
$$\mathcal{I}_n(3) = o_P((\gamma_n^*)^2) \cdot ||\mathcal{U}_2||^2,$$

by noting that

$$\min_{1 \leq j \leq s_{n1}} \widetilde{D}_j > \frac{1}{2} b_{\diamond} n^{1/2}.$$

Hence, by (B.21) and (B.27)–(B.29), we can prove that the leading term of  $\mathcal{I}_n(1) + \mathcal{I}_n(2) + \mathcal{I}_n(3)$  is negative in probability, which indicates that for any  $\epsilon > 0$ , there exists a sufficiently large  $C_* > 0$  such that

(B.30) 
$$\mathsf{P}\Big\{\sup_{(\mathcal{U}_1,\mathcal{U}_2)\in\mathbf{\Omega}_n^*(C_*)} \mathcal{Q}_n^2\big(\mathcal{A}_0 + \gamma_n^*\mathcal{U}_1,\mathcal{B}_0 + \gamma_n^*\mathcal{U}_2/h\big) < \mathcal{Q}_n^2(\mathcal{A}_0,\mathcal{B}_0)\Big\} \ge 1 - \epsilon$$

for large n. Therefore, we may show that

(B.31) 
$$\frac{1}{n} \|\overline{\mathcal{A}}_{n}^{bo} - \mathcal{A}_{0}\|^{2} = \frac{s_{n2}}{nh}, \quad \frac{1}{n} \|\overline{\mathcal{B}}_{n}^{bo} - \mathcal{B}_{0}\|^{2} = \frac{s_{n2}}{nh^{3}},$$

which is (3.2) in Theorem 3.1.

We next complete the proof of Theorem 3.1. Define

(B.32) 
$$\mathcal{M}_{\alpha} = (\alpha_j : 1 \le j \le s_{n2}) \text{ and } \mathcal{M}_{\beta} = (h\beta_j : 1 \le j \le s_{n1}),$$

which correspond the non-zero components in  $\mathcal{A}_0$  and  $\mathcal{B}_0$ , respectively. Let  $\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A}, \mathcal{B}|\mathcal{M}_{\alpha})$ ,  $\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A}, \mathcal{B}|\mathcal{M}_{\beta})$ ,  $\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A}, \mathcal{B}|\alpha_j)$  and  $\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A}, \mathcal{B}|h\beta_j)$  be the gradient vectors of  $\mathcal{L}_n^{\diamond}(\mathcal{A}, \mathcal{B})$  with respect to  $\mathcal{M}_{\alpha}$ ,  $\mathcal{M}_{\beta}$ ,  $\alpha_j$  and  $h\beta_j$ , respectively. Define the sub-gradient of the penalty terms as

$$\mathcal{P}(\mathcal{M}_{\boldsymbol{\alpha}}) = \left[\dot{p}_{\lambda_{4}}(\|\widetilde{\boldsymbol{\alpha}}_{1}\|) \frac{\alpha_{11}}{\|\boldsymbol{\alpha}_{1}\|}, \cdots, \dot{p}_{\lambda_{4}}(\|\widetilde{\boldsymbol{\alpha}}_{s_{n2}}\|) \frac{\alpha_{s_{n2}1}}{\|\boldsymbol{\alpha}_{s_{n2}}\|}, \cdots, \\ \dot{p}_{\lambda_{4}}(\|\widetilde{\boldsymbol{\alpha}}_{1}\|) \frac{\alpha_{1n}}{\|\boldsymbol{\alpha}_{1}\|}, \cdots, \dot{p}_{\lambda_{4}}(\|\widetilde{\boldsymbol{\alpha}}_{s_{n2}}\|) \frac{\alpha_{s_{n2}n}}{\|\boldsymbol{\alpha}_{s_{n2}}\|}\right]^{\mathrm{T}},$$

$$\mathcal{P}(\mathcal{M}_{\boldsymbol{\beta}}) = \left[\dot{p}_{\lambda_{4}}(\widetilde{D}_{1}) \frac{\beta_{11}}{\|\boldsymbol{\beta}_{1}\|}, \cdots, \dot{p}_{\lambda_{4}}(\widetilde{D}_{s_{n1}}) \frac{\beta_{s_{n1}1}}{\|\boldsymbol{\beta}_{s_{n1}}\|}, \cdots, \\ \dot{p}_{\lambda_{4}}(\widetilde{D}_{1}) \frac{\beta_{1n}}{\|\boldsymbol{\beta}_{1}\|}, \cdots, \dot{p}_{\lambda_{4}}(\widetilde{D}_{s_{n1}}) \frac{\beta_{s_{n1}n}}{\|\boldsymbol{\beta}_{s_{n1}}\|}\right]^{\mathrm{T}}.$$

Following the proof of Theorem 1 in Fan et al (2014) (see also the proof of Theorem 1 in Fan and Lv, 2011), the objective function  $\mathcal{Q}_n^2(\mathcal{A}, \mathcal{B})$  has a unique maximiser  $(\overline{\mathcal{A}}_n^{bo}, \overline{\mathcal{B}}_n^{bo})$  if

(B.33) 
$$\dot{\mathcal{L}}_{n}^{\diamond}(\mathcal{A}, \mathcal{B}|\mathcal{M}_{\alpha}) - \mathcal{P}(\mathcal{M}_{\alpha}) = \mathbf{0}_{ns_{n2}},$$

(B.34) 
$$\dot{\mathcal{L}}_{n}^{\diamond}(\mathcal{A}, \mathcal{B}|\mathcal{M}_{\beta}) - \mathcal{P}(\mathcal{M}_{\beta}) = \mathbf{0}_{ns_{n1}},$$

(B.35) 
$$\max_{s_{n2}+1 \leq j \leq d_n} \|\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A}, \mathcal{B}|\alpha_j)\| < \min_{s_{n2}+1 \leq j \leq d_n} \dot{p}_{\lambda_4}(\|\widetilde{\alpha}_j\|),$$

$$(\mathrm{B.36}) \qquad \max_{s_{n1}+1 \leq j \leq d_n} \|\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A}, \mathcal{B}|h\beta_j)\| < \min_{s_{n1}+1 \leq j \leq d_n} \dot{p}_{\lambda_4^*}(\widetilde{D}_j)$$

hold at  $\mathcal{A} = \overline{\mathcal{A}}_n^{bo}$  and  $\mathcal{B} = \overline{\mathcal{B}}_n^{bo}$ . Hence, we next only need to prove (B.33)–(B.36).

By the definition of the biased oracle estimators  $\overline{\mathcal{A}}_n^{bo}$  and  $\overline{\mathcal{B}}_n^{bo}$ , it is easy to verify (B.33) and (B.34). We next only show the proof of (B.35) as the proof of (B.36) is analogous. By Proposition 3.1 and the condition of  $(ns_{n2})^{1/2}\lambda_1 = o(\lambda_4)$ , we may show that

(B.37) 
$$\min_{s_{n2}+1 \le j \le d_n} \dot{p}_{\lambda_4}(\|\widetilde{\alpha}_j\|) = \lambda_4$$

with probability approaching one. On the other hand, for the left hand side of (B.35), we can prove that

$$\max_{s_{n2}+1 \le j \le d_n} \|\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A}, \mathcal{B}|\alpha_j)\| = O_P \Big( h^{-1/2} \big[ (\log h^{-1})^{1/2} + s_{n2}^{1/2} + (nh)^{1/2} s_{n2}^2 \lambda_1^2 \big] \Big)$$

when  $\mathcal{A} = \overline{\mathcal{A}}_n^{bo}$  and  $\mathcal{B} = \overline{\mathcal{B}}_n^{bo}$ . The detailed proof of (B.38) will be given in Appendix C below. Using (B.37), (B.38) and (A.3) in Assumption 6, we may prove (B.35). Then, the proof of Theorem 3.1 is completed.

**Proof of Theorem 3.2.** The proof is similar to the proof of Theorem 2 in Wang and Xia (2009) with some modifications. Recall that  $\overline{a}_{j}^{bo}(U_{k})$ ,  $j=1,\cdots,s_{n2},\ k=1,\cdots,n$ , are the biased oracle estimators of  $a_{j}(U_{k})$  which are obtained by maximising the objective function  $\mathcal{Q}_{n}^{2}(\mathcal{A}^{o},\mathcal{B}^{o})$ .

Let

$$\overline{\mathbf{D}}_{n}^{o} = \left( \max_{1 \le k \le n} \left| \overline{a}_{1}^{bo}(U_{k}) - a_{1}^{uo}(U_{k}) \right|, \cdots, \max_{1 \le k \le n} \left| \overline{a}_{s_{n1}}^{bo}(U_{k}) - a_{s_{n1}}^{uo}(U_{k}) \right| \right)^{\mathrm{T}},$$

and

$$\overline{\mathbf{C}}_{n}^{bo} = \left(\overline{c}_{s_{n1}+1}^{bo}, \cdots, \overline{c}_{s_{n2}}^{bo}\right)^{\mathrm{T}}, \text{ where } \overline{c}_{j}^{bo} = \frac{1}{n} \sum_{k=1}^{n} \overline{a}_{j}^{bo}(U_{k}), \quad j = s_{n1} + 1, \cdots, s_{n2}.$$

By Theorem 3.1, in order to prove (3.3) and (3.4), we only need to show that

(B.39) 
$$\sqrt{nh} \mathbf{B}_n^{\mathrm{T}} \overline{\mathbf{D}}_n^o = o_P(1), \quad \sqrt{n} \mathbf{A}_n^{\mathrm{T}} \left( \overline{\mathbf{C}}_n^{bo} - \mathbf{C}_n^{uo} \right) = o_P(1).$$

For  $k = 1, \dots, n$ , denote

$$\mathbf{a}^{uo}(U_k) = \begin{bmatrix} a_1^{uo}(U_k), \cdots, a_{s_{n_2}}^{uo}(U_k), 0, \cdots, 0 \end{bmatrix}^{\mathrm{T}},$$
  

$$\overline{\mathbf{a}}^{bo}(U_k) = \begin{bmatrix} \overline{a}_1^{bo}(U_k), \cdots, \overline{a}_{s_{n_2}}^{bo}(U_k), 0, \cdots, 0 \end{bmatrix}^{\mathrm{T}},$$

where the last  $d_n - s_{n2}$  elements in the above two vectors are zeros, and let  $\mathbf{b}^{uo}(U_k)$  and  $\overline{\mathbf{b}}^{bo}(U_k)$  be defined analogously. Then, using the first-order condition, we may show that the unbiased oracle estimates satisfy the following equation:

$$(B.40) \quad \mathbf{0}_{s_{n2}} = \mathcal{R}_{s_{n2}} \dot{\mathcal{L}}_{nk} (\widetilde{\mathbf{a}}_k, \widetilde{\mathbf{b}}_k) + \mathcal{R}_{s_{n2}} \ddot{\mathcal{L}}_{nk} (\widetilde{\mathbf{a}}_k, \widetilde{\mathbf{b}}_k) \begin{bmatrix} \mathbf{a}^{uo}(U_k) - \widetilde{\mathbf{a}}_k \\ h \mathbf{b}^{uo}(U_k) - h \widetilde{\mathbf{b}}_k \end{bmatrix}$$

uniformly for  $1 \leq k \leq n$ , where  $\mathcal{R}_{s_{n2}} = \begin{bmatrix} I_{s_{n2}}, \ N_{s_{n2} \times (2d_n - s_{n2})} \end{bmatrix}$  with  $I_s$  being an  $s \times s$  identity matrix and  $N_{r \times s}$  being a  $r \times s$  null matrix.

Following the proof of Theorem 3.1, we can also show that the biased oracle estimates satisfy the following equation:
(B.41)

$$\mathbf{0}_{s_{n2}} = \mathcal{R}_{s_{n2}} \dot{\mathcal{L}}_{nk} \big( \widetilde{\mathbf{a}}_k, \widetilde{\mathbf{b}}_k \big) + \mathcal{R}_{s_{n2}} \ddot{\mathcal{L}}_{nk} \big( \widetilde{\mathbf{a}}_k, \widetilde{\mathbf{b}}_k \big) \left[ \begin{array}{c} \overline{\mathbf{a}}^{bo}(U_k) - \widetilde{\mathbf{a}}_k \\ h \overline{\mathbf{b}}^{bo}(U_k) - h \widetilde{\mathbf{b}}_k \end{array} \right] - \mathcal{P}^*(U_k)$$

uniformly for  $1 \le k \le n$ , where

$$\mathcal{P}^*(U_k) = \left[\dot{p}_{\lambda_4}(\|\widetilde{\boldsymbol{\alpha}}_1\|) \frac{\overline{a}_1^{bo}(U_k)}{\|\overline{\boldsymbol{\alpha}}_1^{bo}\|}, \cdots, \dot{p}_{\lambda_4}(\|\widetilde{\boldsymbol{\alpha}}_{s_{n2}}\|) \frac{\overline{a}_{s_{n2}}^{bo}(U_k)}{\|\overline{\boldsymbol{\alpha}}_{s_{n2}}^{bo}\|}\right]^{\mathrm{T}},$$

 $\overline{\alpha}_j^{bo} = \left[\overline{a}_j^{bo}(U_1), \cdots, \overline{a}_j^{bo}(U_n)\right]^{\mathrm{T}}$ . By Proposition 3.1 and (A.4) in Assumption 6, we may show that

$$\min_{1 \le j \le s_{n2}} \|\widetilde{\boldsymbol{\alpha}}_j\| \ge \min_{1 \le j \le s_{n2}} \|\boldsymbol{\alpha}_{j0}\| - \max_{1 \le j \le s_{n2}} \|\widetilde{\boldsymbol{\alpha}}_j - \boldsymbol{\alpha}_{j0}\| \ge \frac{1}{2} b_{\diamond} \sqrt{n}$$

with probability approaching one, which together with the SCAD structure, indicates that the penalty term  $\mathcal{P}^*(U_k)$  in (B.41) can be asymptotically ignored. Then, by (B.40), (B.41) and the standard argument, we may complete the proof of (B.39).

## APPENDIX C: PROOFS OF SOME TECHNICAL LEMMAS

Define

(C.1) 
$$Z_{ij}(u,l) = Q_{i1}x_{ij}\left(\frac{U_i - u}{h}\right)^l K_h(U_i - u), \quad u \in [0,1]$$

for  $i = 1, ..., n, j = 1, ..., d_n, l = 0, 1, 2, ...,$  where

$$Q_{i1} = q_1 \left[ \sum_{j_1=1}^{d_n} a_{j_1}(U_i) x_{ij_1}, y_i \right].$$

Under different moment conditions on the random element  $Q_{i1}x_{ij}$ , in Lemmas C.1 and C.2 below, we give the uniform consistency results of the non-parametric kernel-based estimators in the ultra-high dimensional case, which are of independent interest. Analogous uniform consistency results also hold when  $Q_{i1}x_{ij}$  in (C.1) is replaced by  $Q_{i2}x_{ij}x_{ik}$  or  $M(X_i, U_i, y_i)x_{ij}x_{ik}x_{il}$ , where  $Q_{i2}$  and  $M(X_i, U_i, y_i)$  are defined in Appendix A of the main document.

**Lemma C.1.** Suppose that Assumptions 1 and 3 in Appendix A are satisfied. Moreover, suppose that the dimension  $d_n \propto n^{\tau_1}$  with  $0 \leq \tau_1 < \infty$ ,  $\mathsf{E}(Q_{i1}|X_i,U_i) = 0$  a.s., the moment condition (A.1) in Appendix A holds for some  $m_0 > 2$ , and

(C.2) 
$$h \propto n^{-\delta_1} \text{ with } 0 < \delta_1 < 1, \quad \frac{nh}{(nd_n)^{2/m_0} \log h^{-1}} \to \infty.$$

Then we have, as  $n \to \infty$ ,

(C.3) 
$$\max_{1 \le j \le d_n} \sup_{u \in [0,1]} \left| \frac{1}{n} \sum_{i=1}^n Z_{ij}(u,l) \right| = O_P\left( \left( \frac{\log h^{-1}}{nh} \right)^{1/2} \right)$$

for any  $l = 0, 1, 2, \cdots$ .

**Proof.** For simplicity, let  $\xi_n = \left(\frac{\log h^{-1}}{nh}\right)^{1/2}$ . The main idea of proving (C.3) is to consider covering the interval [0, 1] by a finite number of subsets U(k) which are centered at  $u_k$  with radius  $r_n = \xi_n h^2$ . Letting  $\mathcal{N}_n$  be the total number of such subsets U(k),  $\mathcal{N}_n = O(r_n^{-1})$ . It is easy to show that

(C.4) 
$$\max_{1 \le j \le d_n} \sup_{u \in [0,1]} \left| \frac{1}{n} \sum_{i=1}^n Z_{ij}(u,l) \right|$$

$$\le \max_{1 \le j \le d_n} \max_{1 \le k \le \mathcal{N}_n} \left| \frac{1}{n} \sum_{i=1}^n Z_{ij}(u_k,l) \right| +$$

$$\max_{1 \le j \le d_n} \max_{1 \le k \le \mathcal{N}_n} \sup_{u \in U(k)} \left| \frac{1}{n} \sum_{i=1}^n Z_{ij}(u,l) - \frac{1}{n} \sum_{i=1}^n Z_{ij}(u_k,l) \right|$$

$$\equiv \prod_{n,1} + \prod_{n,2}.$$

By the continuity condition on  $K(\cdot)$  in Assumption 1 and using the definition of  $r_n$ , we readily have

(C.5) 
$$\Pi_{n2} = O_P(\frac{r_n}{h^2}) = O_P(\xi_n).$$

For  $\Pi_{n1}$ , we apply the truncation technique and the Bernstein inequality for i.i.d. random variables (c.f., Lemma 2.2.9 in van der Vaart and Wellner, 1996) to obtain the convergence rate. Let  $M_n = M_2(nd_n)^{1/m_0}$ ,

$$\overline{Z}_{ij}(u,l) = Z_{ij}(u,l)I\{|Q_{i1}x_{ij}| \le M_n\},$$

$$\widetilde{Z}_{ij}(u,l) = Z_{ij}(u,l) - \overline{Z}_{ij}(u,l),$$

where  $I\{\cdot\}$  is an indicator function and  $M_2$  is some positive constant. Hence we have

(C.6) 
$$\Pi_{n1} \leq \max_{1 \leq j \leq d_n} \max_{1 \leq k \leq \mathcal{N}_n} \left| \frac{1}{n} \sum_{i=1}^n \left\{ \overline{Z}_{ij}(u_k, l) - \mathsf{E}[\overline{Z}_{ij}(u_k, l)] \right\} \right| +$$

$$\max_{1 \leq j \leq d_n} \max_{1 \leq k \leq \mathcal{N}_n} \left| \frac{1}{n} \sum_{i=1}^n \left\{ \widetilde{Z}_{ij}(u_k, l) - \mathsf{E}[\widetilde{Z}_{ij}(u_k, l)] \right\} \right|$$

$$\equiv \Pi_{n3} + \Pi_{n4}.$$

Note that for  $M_3 > 0$  and any  $\varepsilon > 0$ , by (A.1), (C.2) and the Markov inequality,

$$\mathsf{P} \left( \Pi_{n4} > M_3 \xi_n \right) \ \leq \ \sum_{j=1}^{d_n} \sum_{i=1}^n \mathsf{P} \left( \left| Q_{i1} x_{ij} \right| > M_n \right)$$
 
$$\leq \ M_2^{-m_0} \mathsf{E} \left[ \left| Q_{i1} x_{ij} \right|^{m_0} \right] < \varepsilon,$$

if we choose  $M_2 > \mathsf{E} \big[ \big| Q_{i1} x_{ij} \big|^{m_0} \big]^{1/m_0} \varepsilon^{-1/m_0}$ . Then, by letting  $\varepsilon$  be arbitrarily small, we can show that

$$\Pi_{n4} = O_P(\xi_n).$$

Note that

(C.8) 
$$\left| \overline{Z}_{ij}(u_k, l) - \mathsf{E}[\overline{Z}_{ij}(u_k, l)] \right| \le \frac{M_4 M_n}{h}$$

and

(C.9) 
$$\operatorname{Var}\left[\overline{Z}_{ij}(u_k, l)\right] \le \frac{M_4}{h}$$

for some  $M_4 > 0$ . By (C.2), (C.7), (C.8) and Lemma 2.2.9 in van der Vaart and Wellner (1996), we have

(C.10) 
$$P(\Pi_{n3} > M_3 \xi_n) \le 2d_n \mathcal{N}_n \exp\left\{\frac{-n^2 M_3^2 \xi_n^2}{2nM_4/h + 2M_4 M_3 n \xi_n M_n/(3h)}\right\}$$
  
 $\le 2d_n \mathcal{N}_n \exp\left\{-M_3 \log h^{-1}\right\} = o(1),$ 

where  $M_3$  is chosen such that

$$M_3 > 3M_4$$
,  $d_n \mathcal{N}_n \exp\left\{-M_3 \log h^{-1}\right\} = o(1)$ ,

which are possible as  $d_n$  is diverging with a polynomial rate. Hence we have

$$\Pi_{n3} = O_P(\xi_n).$$

In view of (C.4)–(C.7) and (C.11), we have shown (C.3), completing the proof of Lemma C.1.

**Lemma C.2.** Suppose that Assumptions 1 and 3 in Appendix A are satisfied. Moreover, suppose that the dimension  $d_n \propto \exp\{(nh)^{\tau_2}\}$  with  $0 \leq \tau_2 < 1$ ,  $\mathsf{E}(Q_{i1}|X_i,U_i) = 0$  a.s., the moment condition (A.2) in Appendix A holds for all  $m \geq 2$ , and  $h \propto n^{-\delta_1}$  with  $0 < \delta_1 < 1$ . Then we have, as  $n \to \infty$ ,

(C.12) 
$$\max_{1 \le j \le d_n} \sup_{u \in [0,1]} \left| \frac{1}{n} \sum_{i=1}^n Z_{ij}(u,l) \right| = o_P\left( \left( \frac{\log h^{-1}}{nh} \right)^{\tau_3/2} \right)$$

for any  $l = 0, 1, 2, \dots, 0 < \tau_3 < 1 - \tau_2$ .

**Proof.** The proof of (C.12) is similar to the proof of (C.3) in Lemma C.1. The major difference is the way of dealing with  $\Pi_{n1}$ . Because of the stronger moment condition in (A.2), we may directly use a different exponential inequality (Lemma 2.2.11 in van der Vaart and Wellner, 1996) and do not need to apply the truncation method. By replacing  $\xi_n$  by  $\xi_n(\tau_3) \equiv \left(\frac{\log h^{-1}}{nh}\right)^{\tau_3/2}$ , we may re-define  $r = o(\xi_n(\tau_3)h^2)$  and thus  $\mathcal{N}_n = O(r^{-1})$ , where r is the radius used in the finite covering technique (c.f., the proof of Lemma C.1).

Note that there exists a positive constant  $M_5$  such that

(C.13) 
$$\mathsf{E}[|Z_{ij}(u,l)|^m] \le \frac{M_5}{2h} m! (h^{-1})^{m-2}$$

for all  $m \geq 2$ , by using the moment condition (A.2). Then, by (C.13) and Lemma 2.2.11 in van der Vaart and Wellner (1996) with  $M = h^{-1}$  and  $v_i = M_5/h$ , we can show that for any  $\epsilon > 0$ 

(C.14) 
$$P(\Pi_{n1} > \epsilon \xi_n(\tau_3)) \leq 2d_n \mathcal{N}_n \exp\left\{\frac{-n^2 \epsilon^2 \xi_n^2(\tau_3)}{2nM_5/h + 2n\epsilon \xi_n(\tau_3)/h}\right\}$$

$$\leq 2d_n \mathcal{N}_n \exp\left\{-\frac{\epsilon^2 (\log h^{-1})^{\tau_3}}{3M_5} (nh)^{1-\tau_3}\right\}$$

$$= 2\mathcal{N}_n \exp\left\{(nh)^{\tau_2} - \frac{\epsilon^2 \delta_1^{\tau_3} (\log n)^{\tau_3}}{3M_5} (nh)^{1-\tau_3}\right\}$$

$$= o(1)$$

as  $1 - \tau_3 > \tau_2$ . The remaining proof is the same as that in the proof of Lemma C.1. Hence details are omitted here to save space.

**Proof of (B.22)**. To simplify the presentation, we let

$$\widetilde{\mathcal{V}}_n = \mathcal{V}_n (\mathcal{A}_0 - \widetilde{\mathcal{A}}_n, h(\mathcal{B}_0 - \widetilde{\mathcal{B}}_n))$$

and

$$\widetilde{\mathcal{V}}_n(\mathcal{U}_1,\mathcal{U}_2) = \mathcal{V}_n(\mathcal{A}_0 - \widetilde{\mathcal{A}}_n + \gamma_n^* \mathcal{U}_1, \ h(\mathcal{B}_0 - \widetilde{\mathcal{B}}_n) + \gamma_n^* \mathcal{U}_2).$$

Note that

$$\mathcal{I}_n(1) = \mathcal{L}_n^{\diamond} \left( \mathcal{A}_0 + \gamma_n^* \mathcal{U}_1, \mathcal{B}_0 + \gamma_n^* \mathcal{U}_2 / h \right) - \mathcal{L}_n^{\diamond} \left( \mathcal{A}_0, \mathcal{B}_0 \right) \equiv \mathcal{I}_n(1, 1) + \mathcal{I}_n(1, 2)$$

where

$$\mathcal{I}_{n}(1,1) = \gamma_{n}^{*} \mathcal{V}_{n}^{\mathrm{T}}(\mathcal{U}_{1}, \mathcal{U}_{2}) \dot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}), 
\mathcal{I}_{n}(1,2) = \frac{1}{2} \Big[ \widetilde{\mathcal{V}}_{n}^{\mathrm{T}}(\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \widetilde{\mathcal{V}}_{n}(\mathcal{U}_{1}, \mathcal{U}_{2}) - \widetilde{\mathcal{V}}_{n}^{\mathrm{T}} \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \widetilde{\mathcal{V}}_{n} \Big].$$

By Taylor's expansion, we have

$$\mathcal{I}_{n}(1,1) = \gamma_{n}^{*} \mathcal{V}_{n}^{\Gamma}(\mathcal{U}_{1}, \mathcal{U}_{2}) \dot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) 
= \gamma_{n}^{*} \mathcal{V}_{n}^{\Gamma}(\mathcal{U}_{1}, \mathcal{U}_{2}) \dot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0}) - \gamma_{n}^{*} \mathcal{V}_{n}^{\Gamma}(\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0}) \widetilde{\mathcal{V}}_{n} + o_{P}((\gamma_{n}^{*})^{2}) \cdot (\|\mathcal{U}_{1}\|^{2} + \|\mathcal{U}_{2}\|^{2}),$$

where  $V_n(U_1, U_2)$  is defined in Section 2.2 of the main document. On the other hand, by some elementary calculations, we also have

$$\mathcal{I}_{n}(1,2) = \frac{1}{2} \Big[ \widetilde{\mathcal{V}}_{n}^{\Gamma} (\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \widetilde{\mathcal{V}}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) - \widetilde{\mathcal{V}}_{n}^{\Gamma} \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \widetilde{\mathcal{V}}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) \Big] + \\
+ \frac{1}{2} \Big[ \widetilde{\mathcal{V}}_{n}^{\Gamma} \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \widetilde{\mathcal{V}}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) - \widetilde{\mathcal{V}}_{n}^{\Gamma} \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \widetilde{\mathcal{V}}_{n} \Big] \\
= \frac{\gamma_{n}^{*}}{2} \widetilde{\mathcal{V}}_{n}^{\Gamma} (\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \widetilde{\mathcal{V}}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) + \\
+ \frac{\gamma_{n}^{*}}{2} \widetilde{\mathcal{V}}_{n}^{\Gamma} \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \mathcal{V}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) \\
= \frac{1}{2} (\gamma_{n}^{*})^{2} \mathcal{V}_{n}^{\Gamma} (\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \mathcal{V}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) + \\
+ \gamma_{n}^{*} \widetilde{\mathcal{V}}_{n}^{\Gamma} \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \mathcal{V}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) \\
= \frac{1}{2} (\gamma_{n}^{*})^{2} \mathcal{V}_{n}^{\Gamma} (\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n}) \mathcal{V}_{n} (\mathcal{U}_{1}, \mathcal{U}_{2}) + \\
+ \gamma_{n}^{*} \mathcal{V}_{n}^{\Gamma} (\mathcal{U}_{1}, \mathcal{U}_{2}) \ddot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0}) \widetilde{\mathcal{V}}_{n} + o_{P} ((\gamma_{n}^{*})^{2}) \cdot (\|\mathcal{U}_{1}\|^{2} + \|\mathcal{U}_{2}\|^{2}).$$

We can easily prove (B.22) by using the above two results on the asymptotic expansion for  $\mathcal{I}_n(1,1)$  and  $\mathcal{I}_n(1,2)$ .

**Proof** (B.23). Recall that

(C.15) 
$$\mathcal{I}_n(4) = \gamma_n^* \mathcal{V}_n^{\Gamma}(\mathcal{U}_1, \mathcal{U}_2) \dot{\mathcal{L}}_n(\mathcal{A}_0, \mathcal{B}_0).$$

By Taylor's expansion for  $q_1(\cdot, \cdot)$  and Assumption 4, when  $|U_i - U_k| = O(h)$ , we have

$$q_{1} \left\{ \sum_{j=1}^{d_{n}} \left[ a_{j}(U_{k}) + \dot{a}_{j}(U_{k})(U_{i} - U_{k}) \right] x_{ij}, \ y_{i} \right\}$$

$$= q_{1} \left\{ \sum_{j=1}^{s_{n2}} \left[ a_{j}(U_{k}) + \dot{a}_{j}(U_{k})(U_{i} - U_{k}) \right] x_{ij}, \ y_{i} \right\}$$

$$= q_{1} \left[ \sum_{j=1}^{s_{n2}} a_{j}(U_{i}) x_{ij}, \ y_{i} \right] + O_{P}(s_{n2}h^{2})$$

$$(C.16) \qquad \equiv Q_{i1} + O_{P}(s_{n2}h^{2}),$$

which implies that

$$\mathcal{I}_{n}(4) = \frac{\gamma_{n}^{*}}{n} \sum_{k=1}^{n} \sum_{i=1}^{n} Q_{i1} X_{i}^{\mathrm{T}} \mathbf{u}_{1}(k) K_{h}(U_{i} - U_{k}) + \frac{\gamma_{n}^{*}}{n} \sum_{k=1}^{n} \sum_{i=1}^{n} Q_{i1} X_{i}^{\mathrm{T}} \mathbf{u}_{2}(k) \left(\frac{U_{i} - U_{k}}{h}\right) K_{h}(U_{i} - U_{k}) + O_{P}(\gamma_{n}^{*} s_{n2}^{3/2} n^{1/2} h^{2}) \cdot (\|\mathcal{U}_{1}\| + \|\mathcal{U}_{2}\|).$$
(C.17)

Note that  $(U_i, X_i, y_i)$ ,  $i = 1, \dots, n$ , are independent and identically distributed. By Assumptions 1, 2(i) and 3 in Appendix A, and the Cauchy-Schwarz inequality, we have

$$\begin{split} & \mathsf{E}\Big[\frac{1}{n}\sum_{k=1}^{n}\sum_{i=1}^{n}Q_{i1}X_{i}^{\mathsf{T}}\mathbf{u}_{1}(k)K_{h}(U_{i}-U_{k})\Big]^{2} \\ \leq & \frac{1}{n}\sum_{k=1}^{n}\mathsf{E}\Big[\sum_{i=1}^{n}Q_{i1}X_{i}^{\mathsf{T}}\mathbf{u}_{1}(k)K_{h}(U_{i}-U_{k})\Big]^{2} \\ = & \frac{1}{n}\sum_{k=1}^{n}\mathsf{E}\Big(\mathsf{E}\Big\{\Big[\sum_{i=1}^{n}Q_{i1}X_{i}^{\mathsf{T}}\mathbf{u}_{1}(k)K_{h}(U_{i}-U_{k})\Big]^{2}\Big|U_{k}\Big\}\Big) \\ = & \frac{1}{n}\sum_{k=1}^{n}\sum_{i=1}^{n}\mathsf{E}\Big\{\mathsf{E}\Big[Q_{i1}^{2}\mathbf{u}_{1}^{\mathsf{T}}(k)X_{i}X_{i}^{\mathsf{T}}\mathbf{u}_{1}(k)K_{h}^{2}(U_{i}-U_{k})\Big|U_{k}\Big]\Big\} \\ = & O(s_{n2}h^{-1})\cdot\|\mathcal{U}_{1}\|^{2}. \end{split}$$

Similarly, we can also show that

$$\mathsf{E} \Big[ \frac{1}{n} \sum_{k=1}^{n} \sum_{i=1}^{n} Q_{i1} X_{i}^{\mathsf{T}} \mathbf{u}_{2}(k) \Big( \frac{U_{i} - U_{k}}{h} \Big) K_{h} (U_{i} - U_{k}) \Big]^{2} = O(s_{n2}h^{-1}) \cdot \|\mathcal{U}_{2}\|^{2}.$$

Noting that  $s_{n2}h^2 \propto (nh)^{-1/2}$ , we have

(C.18) 
$$\mathcal{I}_n(4) = O_P((\gamma_n^*)^2 n^{1/2}) \cdot (\|\mathcal{U}_1\| + \|\mathcal{U}_2\|),$$

which completes the proof of (B.23).

**Proof** (B.38). Let

$$\dot{\mathcal{L}}_n(\mathcal{A},\mathcal{B}|\boldsymbol{\alpha}_j) = \left[\dot{\mathcal{L}}_{n1}(\mathbf{a}_1,\mathbf{b}_1,j),\cdots,\dot{\mathcal{L}}_{nn}(\mathbf{a}_n,\mathbf{b}_n,j)\right]^{\mathrm{T}},$$

where  $\dot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k, j)$  is the j-th element of  $\dot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k)$  defined in Section 2.2 of the main document; and let

$$\ddot{\mathcal{L}}_n(\mathcal{A},\mathcal{B}|\boldsymbol{lpha}_j) = \operatorname{diag}\left\{\ddot{\mathcal{L}}_{n1}(\mathbf{a}_1,\mathbf{b}_1,j),\cdots,\ddot{\mathcal{L}}_{nn}(\mathbf{a}_n,\mathbf{b}_n,j)\right\},$$

where  $\ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k, j)$  is the *j*-th row of  $\ddot{\mathcal{L}}_{nk}(\mathbf{a}_k, \mathbf{b}_k)$  defined in Section 2.2. Observe that (C.19)

$$\dot{\mathcal{L}}_n^{\diamond}(\mathcal{A},\mathcal{B}|\boldsymbol{\alpha}_j) = \dot{\mathcal{L}}_n(\widetilde{\mathcal{A}}_n,\widetilde{\mathcal{B}}_n|\boldsymbol{\alpha}_j) + \ddot{\mathcal{L}}_n(\widetilde{\mathcal{A}}_n,\widetilde{\mathcal{B}}_n|\boldsymbol{\alpha}_j) \left[ \mathcal{V}_n(\mathcal{A},h\mathcal{B}) - \mathcal{V}_n(\widetilde{\mathcal{A}}_n,h\widetilde{\mathcal{B}}_n) \right].$$

By Taylor's expansion of  $q_1(\cdot, \cdot)$  and Proposition 3.1, and following the argument in the proof of (B.22) above, we have

$$\dot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n} | \boldsymbol{\alpha}_{j}) = \dot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0} | \boldsymbol{\alpha}_{j}) + \ddot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0} | \boldsymbol{\alpha}_{j}) \left[ \mathcal{V}_{n}(\widetilde{\mathcal{A}}_{n}, h\widetilde{\mathcal{B}}_{n}) - \mathcal{V}_{n}(\mathcal{A}_{0}, h\mathcal{B}_{0}) \right] 
+ O_{P}(s_{n2}^{2} \lambda_{1}^{2}) \cdot I_{n},$$

where  $I_n$  is an  $n \times n$  identity matrix. Similarly, we may also show that

$$\ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n} | \boldsymbol{\alpha}_{j}) \left[ \mathcal{V}_{n}(\mathcal{A}, h\mathcal{B}) - \mathcal{V}_{n}(\widetilde{\mathcal{A}}_{n}, h\widetilde{\mathcal{B}}_{n}) \right] \\
= \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n}, \widetilde{\mathcal{B}}_{n} | \boldsymbol{\alpha}_{j}) \left[ \mathcal{V}_{n}(\mathcal{A}, h\mathcal{B}) - \mathcal{V}_{n}(\mathcal{A}_{0}, h\mathcal{B}_{0}) \right] - \\
(C.21) \ddot{\mathcal{L}}_{n}(\mathcal{A}_{0}, \mathcal{B}_{0} | \boldsymbol{\alpha}_{j}) \left[ \mathcal{V}_{n}(\widetilde{\mathcal{A}}_{n}, h\widetilde{\mathcal{B}}_{n}) - \mathcal{V}_{n}(\mathcal{A}_{0}, h\mathcal{B}_{0}) \right] + O_{P}(s_{n2}^{2} \lambda_{1}^{2}) \cdot I_{n}.$$

By (C.19)-(C.21), we may show that

$$\dot{\mathcal{L}}_{n}^{\diamond}(\mathcal{A},\mathcal{B}|\boldsymbol{\alpha}_{j}) = \dot{\mathcal{L}}_{n}(\mathcal{A}_{0},\mathcal{B}_{0}|\boldsymbol{\alpha}_{j}) + \ddot{\mathcal{L}}_{n}(\widetilde{\mathcal{A}}_{n},\widetilde{\mathcal{B}}_{n}|\boldsymbol{\alpha}_{j}) \left[ \mathcal{V}_{n}(\mathcal{A},h\mathcal{B}) - \mathcal{V}_{n}(\mathcal{A}_{0},h\mathcal{B}_{0}) \right] \\
+ O_{P}(s_{n,2}^{2}\lambda_{1}^{2}) \cdot I_{n}.$$

By (B.5) and the standard argument in the kernel-based smoothing, we have

(C.23) 
$$\max_{s_{n2}+1 \le j \le d_n} \left\| \dot{\mathcal{L}}_n(\mathcal{A}_0, \mathcal{B}_0 | \boldsymbol{\alpha}_j) \right\| = O_P \left( h^{-1/2} \sqrt{\log h^{-1}} \right).$$

By (A.5) in Assumption 6(ii) and (B.31), we may also show that (C.24)

$$\max_{s_{n2}+1 \le j \le d_n} \left\| \ddot{\mathcal{L}}_n(\widetilde{\mathcal{A}}_n, \widetilde{\mathcal{B}}_n | \alpha_j) \left[ \mathcal{V}_n(\mathcal{A}, h\mathcal{B}) - \mathcal{V}_n(\mathcal{A}_0, h\mathcal{B}_0) \right] \right\| = O_P \left( h^{-1/2} s_{n2}^{1/2} \right)$$

when  $\mathcal{A} = \overline{\mathcal{A}}_n^{bo}$  and  $\mathcal{B} = \overline{\mathcal{B}}_n^{bo}$ .

Using 
$$(C.22)$$
– $(C.24)$ , we may complete the proof of  $(B.38)$ .

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