

# Marginal Quantile Regression for Varying Coefficient Models with Longitudinal Data

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## Supplementary Material: proofs and additional tables

### Appendix A. Notations

For any real-valued function  $f$  on  $[0,1]$ , let  $\|f\|_\infty = \sup_{x \in [0,1]} |f(x)|$ . Let  $\|\cdot\|_2$  be the  $L_2$  norm for functions and  $l_2$  norm for vectors. For any matrix  $\mathbf{A}$ ,  $\|\mathbf{A}\|$  denotes the modulus of the largest singular value of  $\mathbf{A}$ . We use  $c, c_1, c_2$  to denote generic positive constants which can take different values at different places. Note that by Condition (C3) and the result of De Boor (2001) (P. 149), there exists a constant  $c$  such that

$$\sup_{t \in [0,1]} |\alpha_l(t) - \mathbf{B}_l^T(t) \boldsymbol{\gamma}_l^0| \leq ch^r, \quad l = 1, \dots, p, \quad (\text{S.1})$$

where  $\boldsymbol{\gamma}_l^0$  can be viewed as the best approximation coefficient vector for  $\alpha_l(t)$ .

Let  $\boldsymbol{\gamma}_0 = (\boldsymbol{\gamma}_1^{0T}, \dots, \boldsymbol{\gamma}_p^{0T})$ ,  $\boldsymbol{\mu}_i^0 = (\mu_{i1}^0, \dots, \mu_{im_i}^0)^T$  with  $\mu_{ij}^0 = \mathbf{X}_{ij}^T \boldsymbol{\alpha}(t_{ij})$  and  $\boldsymbol{\epsilon}_i = \mathbf{y}_i - \boldsymbol{\mu}_i^0$ . Denote  $\mathbf{S}_k(\boldsymbol{\gamma}) = \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik}(\boldsymbol{\gamma})$ , where  $\mathbf{S}_{ik}(\boldsymbol{\gamma}) = \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \psi_\tau(\mathbf{y}_i - \mathbf{U}_i \boldsymbol{\gamma})$ .

Similarly write  $\mathbf{S}^0(\boldsymbol{\gamma}) = (\mathbf{S}_1^{0T}(\boldsymbol{\gamma}), \dots, \mathbf{S}_v^{0T}(\boldsymbol{\gamma}))^T$  with  $\mathbf{S}_k^0(\boldsymbol{\gamma}) = \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik}^0(\boldsymbol{\gamma})$ , where

$$\mathbf{S}_{ik}^0(\boldsymbol{\gamma}) = \mathbf{S}_{ik1}^0 + \mathbf{S}_{ik2}^0 + \mathbf{S}_{ik3}^0(\boldsymbol{\gamma}), \quad \mathbf{S}_{ik1}^0 = \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \psi_\tau(\boldsymbol{\epsilon}_i),$$

$$\mathbf{S}_{ik2}^0 = \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \boldsymbol{\Gamma}_i (\boldsymbol{\mu}_i^0 - \mathbf{U}_i \boldsymbol{\gamma}_0), \quad \mathbf{S}_{ik3}^0(\boldsymbol{\gamma}) = \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \boldsymbol{\Gamma}_i (\mathbf{U}_i \boldsymbol{\gamma}_0 - \mathbf{U}_i \boldsymbol{\gamma}).$$

Then we denote

$$\mathbf{S}_{k1}^0 = \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik1}^0, \quad \mathbf{S}_{k2}^0 = \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik2}^0 \quad \text{and} \quad \mathbf{S}_{k3}^0(\boldsymbol{\gamma}) = \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik3}^0(\boldsymbol{\gamma}).$$

Define the set  $\Theta_n(C) = \{\gamma : \|\mathbf{B}^T(\gamma - \gamma_0)\|_2 = C/\sqrt{nh}\}$  for a sufficiently large constant  $C$ , where  $\mathbf{B}(t) = (\mathbf{B}_1^T(t), \dots, \mathbf{B}_p^T(t))^T$  and

$$\|\mathbf{B}^T(\gamma - \gamma_0)\|_2 = \left( \int \left[ \sum_{l=1}^p \sum_{k=1}^{K_l} B_{lk}(t)(\gamma_{lk} - \gamma_{lk}^0) \right]^2 dt \right)^{1/2}.$$

Let

$$\Sigma_{kk'}(\gamma) = \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik}(\gamma) \mathbf{S}_{ik'}^T(\gamma) \quad \text{and} \quad \Sigma_{kk'}^0 = \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik1}^0 \mathbf{S}_{ik'1}^{0T}$$

be the  $(k, k')$ -block of

$$\Sigma_n(\gamma) = \{\Sigma_{kk'}(\gamma)\}_{k,k'=1}^v \quad \text{and} \quad \Sigma_n^0 = \{\Sigma_{kk'}^0\}_{k,k'=1}^v, \quad (\text{S.2})$$

respectively. Finally, we define

$$\mathbf{Q}_n^0(\gamma) = n(\mathbf{S}^0(\gamma))^T \{\Sigma_n^0\}^{-1} \mathbf{S}^0(\gamma). \quad (\text{S.3})$$

## Appendix B. Lemmas

The following lemmas are needed in preparation for the proof of the theorems.

**Lemma 1.** Assume Conditions (C1), (C3), (C5) and (C6) hold. There exist two constants  $0 < c_1 \leq c_2$ , such that, except in an event whose probability tends to zero as  $n \rightarrow \infty$ ,

$$c_1 \|\gamma\|_2^2 \leq \|\mathbf{B}^T \gamma\|_2^2 \leq c_2 \|\gamma\|_2^2,$$

for any vector  $\gamma$  with length  $\sum_{l=1}^p J_l$ , where  $\|\mathbf{B}^T \gamma\|_2^2 = \int (\sum_{l=1}^p \sum_{k=1}^{K_l} B_{lk}(t) \gamma_{lk})^2 dt$ . Furthermore, there also exist two constants  $0 < c'_1 \leq c'_2$ , such that, except in an event whose probability tends to zero as  $n \rightarrow \infty$ ,

$$c'_1 \|\gamma\|_2^2 \leq \|\mathbf{B}^T \gamma\|_n^2 \leq c'_2 \|\gamma\|_2^2,$$

where  $\|\mathbf{B}^T \gamma\|_n^2 = \frac{1}{n} \sum_{i=1}^n \frac{1}{m_i} \sum_{j=1}^{m_i} (\mathbf{B}^T(t_{ij}) \gamma)^2$ .

*Proof.* The results can be proved along the lines of Lemmas 3 and 6 in Xue et al. (2010).  $\square$

**Lemma 2.** Assume that Conditions (C1)-(C7) hold, then one has

$$\|\mathbf{S}_{k1}^0\|_2 = O_p(1/\sqrt{n}), \quad \|\mathbf{S}_{k2}^0\|_2 = O_p(h^r).$$

Furthermore, there exist two constants  $0 < c_1 \leq c_2$  such that for any  $\boldsymbol{\gamma} \in \Theta_n(C)$ ,

$$c_1 C/\sqrt{nh} \leq \|\mathbf{S}_{k3}^0(\boldsymbol{\gamma})\|_2 \leq c_2 C/\sqrt{nh},$$

except in an event whose probability goes to 0 as  $n \rightarrow \infty$ .

*Proof.* By (C2), (C4) and (C7), we have

$$E(\mathbf{S}_{k1}^0) = 0 \quad \text{and} \quad \text{tr}(E(\mathbf{S}_{k1}^0 \mathbf{S}_{k1}^{0T})) = \text{tr}(E\mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \psi_\tau(\boldsymbol{\epsilon}_i) \psi_\tau^T(\boldsymbol{\epsilon}_i) \mathbf{M}_{ki}^T \boldsymbol{\Gamma}_i \mathbf{U}_i) = O(1).$$

Therefore, we obtain  $E\|\mathbf{S}_{k1}^0\|_2^2 = \text{tr}(E(\mathbf{S}_{k1}^0 \mathbf{S}_{k1}^{0T}))/n = O(1/n)$  which implies  $\|\mathbf{S}_{k1}^0\|_2 = O_p(1/\sqrt{n})$ .

For  $\mathbf{S}_{k2}^0$ , by Lemma 1, equation (S.1) and the Conditions (C4) and (C7), applying the Cauchy-Schwartz inequality, we have

$$\begin{aligned} |\boldsymbol{\nu}^T \mathbf{S}_{k2}^0| &= \left| \frac{1}{n} \sum_{i=1}^n \boldsymbol{\nu}^T \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \boldsymbol{\Gamma}_i (\boldsymbol{\mu}_i^0 - \mathbf{U}_i \boldsymbol{\gamma}_0) \right| \\ &\leq \left( \frac{1}{n} \sum_i \boldsymbol{\nu}^T \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \mathbf{M}_{ki}^T \boldsymbol{\Gamma}_i \mathbf{U}_i \boldsymbol{\nu} \right)^{1/2} \left( \frac{1}{n} \sum_i (\boldsymbol{\mu}_i^0 - \mathbf{U}_i \boldsymbol{\gamma}_0)^T \boldsymbol{\Gamma}_i \boldsymbol{\Gamma}_i^T (\boldsymbol{\mu}_i^0 - \mathbf{U}_i \boldsymbol{\gamma}_0) \right)^{1/2} \\ &\leq c (\boldsymbol{\nu}^T \boldsymbol{\nu})^{1/2} \|\mathbf{B}^T(t) \boldsymbol{\gamma}_0 - \boldsymbol{\alpha}(t)\|_\infty \\ &\leq ch^r. \end{aligned}$$

It follows that  $\|\mathbf{S}_{k2}^0\|_2 = O_p(h^r)$ .

Similarly, by the Cauchy-Schwartz inequality, on the set  $\Theta_n(C)$ , we can prove that there exist a constant  $c_2$  such that  $\|\mathbf{S}_{k3}^0(\boldsymbol{\gamma})\|_2 \leq c_2 C/\sqrt{nh}$ .

On the other hand, taking  $\boldsymbol{\nu} = (\boldsymbol{\gamma} - \boldsymbol{\gamma}_0)/\|\boldsymbol{\gamma} - \boldsymbol{\gamma}_0\|_2$ , Conditions (C4)-(C7) and Lemma 1 entail that there exists a positive constant  $c_1$  such that  $|\boldsymbol{\nu}^T \mathbf{S}_{k3}^0(\boldsymbol{\gamma})| \geq c_1 C/\sqrt{nh}$ . Therefore, we obtain  $\|\mathbf{S}_{k3}^0(\boldsymbol{\gamma})\|_2 \geq c_1 C/\sqrt{nh}$ . This completes the proof.  $\square$

**Lemma 3.** Assume that Conditions (C1)-(C7) hold, the eigenvalues of  $\boldsymbol{\Sigma}_n^0$  are bounded from 0 and infinity with probability approaching 1. And, on the set  $\Theta_n(C)$ , we have  $\|\mathbf{S}^0(\boldsymbol{\gamma})\|_2 = O_p(1/\sqrt{nh})$  and  $\mathbf{Q}_n^0(\boldsymbol{\gamma}) = O_p(1/h)$ .

*Proof.* By Lemma 1 and the definition of  $\boldsymbol{\Sigma}_n^0$  in (S.2), we can easily conclude that  $\boldsymbol{\Sigma}_n^0$  has eigenvalues bounded away from 0 and infinity. In addition,  $\mathbf{S}^0(\boldsymbol{\gamma}) = O_p(1/\sqrt{nh})$  follows directly from Lemma 2, and  $\mathbf{Q}_n^0(\boldsymbol{\gamma}) = O_p(1/h)$  follows from the above two results.  $\square$

**Lemma 4.** Assume that Conditions (C1)-(C7) hold. On the set  $\Theta_n(C)$  for some  $C$  sufficiently large, we have

$$\sup_{\gamma \in \Theta_n(C)} \|\mathbf{S}(\gamma) - \mathbf{S}^0(\gamma)\|_2 = o_p(1/\sqrt{nh}), \quad (\text{S.4})$$

$$\sup_{\gamma \in \Theta_n(C)} |\mathbf{Q}_n(\gamma) - \mathbf{Q}_n^0(\gamma)| = o_p(1/h). \quad (\text{S.5})$$

*Proof.* We only need to consider the components  $\mathbf{S}_k(\gamma) - \mathbf{S}_k^0(\gamma)$  of  $\mathbf{S}(\gamma) - \mathbf{S}^0(\gamma)$ ,  $k = 1, \dots, v$ .

For any  $\boldsymbol{\nu} \in \mathbb{R}^{\sum_{i=1}^p K_i}$  with  $\boldsymbol{\nu}^T \boldsymbol{\nu} = 1$ , we write

$$\boldsymbol{\nu}^T (\mathbf{S}_k(\gamma) - \mathbf{S}_k^0(\gamma)) = \boldsymbol{\nu}^T \boldsymbol{\zeta} + \eta, \quad (\text{S.6})$$

where

$$\boldsymbol{\zeta} = \frac{1}{n} \sum_{i=1}^n \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \{ \psi_\tau(\mathbf{y}_i - \mathbf{U}_i \boldsymbol{\gamma}) - \psi_\tau(\boldsymbol{\epsilon}_i) + [F_i(\mathbf{U}_i \boldsymbol{\gamma} - \boldsymbol{\mu}_i^0) - F_i(0)] \},$$

$$\eta = \frac{1}{n} \sum_{i=1}^n \boldsymbol{\nu}^T \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \{ -\boldsymbol{\Gamma}_i(\boldsymbol{\mu}_i^0 - \mathbf{U}_i \boldsymbol{\gamma}) - [F_i(\mathbf{U}_i \boldsymbol{\gamma} - \boldsymbol{\mu}_i^0) - F_i(0)] \},$$

and  $F_i(\mathbf{U}_i \boldsymbol{\gamma} - \boldsymbol{\mu}_i^0) = (F_{i1}(\mathbf{U}_{i1}^T \boldsymbol{\gamma} - \boldsymbol{\mu}_{i1}^0), \dots, F_{im_i}(\mathbf{U}_{im_i}^T \boldsymbol{\gamma} - \boldsymbol{\mu}_{im_i}^0))^T$  with  $F_{ij}(\cdot)$  being the conditional cdf of  $\epsilon_{ij}$ .

Since  $|\boldsymbol{\mu}_{ij}^0 - \mathbf{U}_{ij}^T \boldsymbol{\gamma}| = O_p(1/\sqrt{nh})$  on the set  $\Theta_n(C)$ , by the Taylor expansion, we get

$$F_i(\mathbf{U}_i \boldsymbol{\gamma} - \boldsymbol{\mu}_i^0) - F_i(0) = -\boldsymbol{\Gamma}_i(\boldsymbol{\mu}_i^0 - \mathbf{U}_i \boldsymbol{\gamma}) + O_p(1/(nh)). \quad (\text{S.7})$$

By Lemma 6.2 of He and Shi (1996) together with Condition (C4), we have

$$\sup_{1 \leq i \leq n} \|\mathbf{U}_i\| = O_p(h^{-1/2}). \quad (\text{S.8})$$

Applying Lemma 19.24 of Van der Vaart (2000), we have

$$\sup_{\gamma \in \Theta_n(C)} \left| \frac{1}{n} \sum_{i=1}^n \{ \psi_\tau(\mathbf{y}_i - \mathbf{U}_i \boldsymbol{\gamma}) - \psi_\tau(\boldsymbol{\epsilon}_i) + [F_i(\mathbf{U}_i \boldsymbol{\gamma} - \boldsymbol{\mu}_i^0) - F_i(0)] \} \right| = o_p(n^{-1/2}). \quad (\text{S.9})$$

Therefore, by Conditions (C2) and (C7) together with (S.8), we obtain

$$\sup_{\boldsymbol{\nu}^T \boldsymbol{\nu} = 1, \gamma \in \Theta_n(C)} \boldsymbol{\nu}^T \boldsymbol{\zeta} = O_p(h^{-1/2}) \times o_p(n^{-1/2}) = o_p(1/\sqrt{nh}). \quad (\text{S.10})$$

On the other hand, for the term  $\eta$  in (S.6), by (S.7) and (S.8), we get

$$\sup_{\boldsymbol{\nu}^T \boldsymbol{\nu}=1, \boldsymbol{\gamma} \in \Theta_n(C)} |\eta| = O_p(h^{-1/2}) \times O_p(1/(nh)) = o_p(1/\sqrt{nh}). \quad (\text{S.11})$$

Hence, combining (S.6)-(S.11), we obtain

$$\sup_{\boldsymbol{\nu}^T \boldsymbol{\nu}=1, \boldsymbol{\gamma} \in \Theta_n(C)} \boldsymbol{\nu}^T (\mathbf{S}_k(\boldsymbol{\gamma}) - \mathbf{S}_k^0(\boldsymbol{\gamma})) = o_p(1/\sqrt{nh}),$$

and it follows that (S.4) holds.

Next, we prove (S.5). Notice that

$$\begin{aligned} \|\boldsymbol{\Sigma}_n^{-1}(\boldsymbol{\gamma}) - \{\boldsymbol{\Sigma}_n^0\}^{-1}\| &= \|\boldsymbol{\Sigma}_n^{-1}(\boldsymbol{\gamma})[\boldsymbol{\Sigma}_n(\boldsymbol{\gamma}) - \boldsymbol{\Sigma}_n^0]\{\boldsymbol{\Sigma}_n^0\}^{-1}\| \\ &\leq \|\boldsymbol{\Sigma}_n^{-1}(\boldsymbol{\gamma})\| \|\boldsymbol{\Sigma}_n(\boldsymbol{\gamma}) - \boldsymbol{\Sigma}_n^0\| \|\{\boldsymbol{\Sigma}_n^0\}^{-1}\|. \end{aligned}$$

Consider the  $(k, k')$ -block of  $\{\boldsymbol{\Sigma}_n(\boldsymbol{\gamma}) - \boldsymbol{\Sigma}_n^0\}$ , by the definitions of  $\boldsymbol{\Sigma}_{kk'}(\boldsymbol{\gamma})$  and  $\boldsymbol{\Sigma}_{kk'}^0$ , as in the proof of the first part of the lemma, by some careful calculations, we can show that

$$\|\boldsymbol{\Sigma}_{kk'}(\boldsymbol{\gamma}) - \boldsymbol{\Sigma}_{kk'}^0\| = o_p(1).$$

Therefore, we have

$$\|\boldsymbol{\Sigma}_n(\boldsymbol{\gamma}) - \boldsymbol{\Sigma}_n^0\| = o_p(1).$$

Based on Lemma 3, the eigenvalues of  $\boldsymbol{\Sigma}_n^0$  are bounded from 0 and infinity, therefore we can conclude that the eigenvalues of  $\boldsymbol{\Sigma}_n(\boldsymbol{\gamma})$  are also bounded from 0 and infinity, which leads to

$$\|\boldsymbol{\Sigma}_n^{-1}(\boldsymbol{\gamma}) - \{\boldsymbol{\Sigma}_n^0\}^{-1}\| = o_p(1). \quad (\text{S.12})$$

Finally, by the definitions of  $\mathbf{Q}_n(\boldsymbol{\gamma})$  and  $\mathbf{Q}_n^0(\boldsymbol{\gamma})$ , (S.5) holds by (S.4), (S.12) and Lemma 2.  $\square$

**Lemma 5.** For any small positive  $\varepsilon$ , there exist constants  $\varrho$  and  $C$  such that

$$P \left\{ \inf_{\boldsymbol{\gamma} \in \Theta_n(C)} \mathbf{Q}_n^0(\boldsymbol{\gamma}) > \mathbf{Q}_n^0(\boldsymbol{\gamma}_0) + \frac{\varrho}{h} \right\} > 1 - \varepsilon,$$

for  $n$  large enough.

*Proof.* Let  $\mathbf{\Delta}(\gamma) = \mathbf{S}^0(\gamma) - \mathbf{S}^0(\gamma_0)$ . Then we can write

$$\frac{1}{n} \{ \mathbf{Q}_n^0(\gamma) - \mathbf{Q}_n^0(\gamma_0) \} = \mathbf{\Delta}^T(\gamma)(\mathbf{\Sigma}_n^0)^{-1} \mathbf{\Delta}(\gamma) + 2\mathbf{\Delta}^T(\gamma)(\mathbf{\Sigma}_n^0)^{-1} \mathbf{S}^0(\gamma_0).$$

According to the definitions of  $\mathbf{S}^0(\gamma)$  and  $\mathbf{S}^0(\gamma_0)$ , one has  $\mathbf{\Delta}(\gamma) = \mathbf{S}_{k3}^0(\gamma)$ . By Lemma 3, the eigenvalues of  $\{\mathbf{\Sigma}_n^0\}^{-1}$  are bounded, hence on the set  $\Theta_n(C)$

$$\begin{aligned} |\mathbf{\Delta}^T(\gamma)(\mathbf{\Sigma}_n^0)^{-1} \mathbf{S}^0(\gamma_0)| &= O_p(\sum_{k=1}^v \|\mathbf{S}_{k3}^0(\gamma)\|_2 (\|\mathbf{S}_{k1}^0\|_2 + \|\mathbf{S}_{k2}^0\|_2)) \\ &= O_p(C/(nh)), \end{aligned}$$

by Lemma 2.

On the other hand,

$$\mathbf{\Delta}^T(\gamma)(\mathbf{\Sigma}_n^0)^{-1} \mathbf{\Delta}(\gamma) \asymp \sum_{k=1}^v \|\mathbf{S}_{k3}^0(\gamma)\|_2^2 \asymp \frac{C^2}{nh},$$

again by Lemma 2. Choosing  $C$  sufficiently large, we can obtain the desired result. This completes the proof.  $\square$

**Lemma 6.** For any  $\varepsilon > 0$ , there exists  $C$  such that

$$P \left\{ \inf_{\gamma \in \Theta_n(C)} \mathbf{Q}_n(\gamma) > \mathbf{Q}_n(\gamma_0) \right\} > 1 - \varepsilon.$$

*Proof.* Note that we can write

$$\mathbf{Q}_n(\gamma) - \mathbf{Q}_n(\gamma_0) = \mathbf{Q}_n(\gamma) - \mathbf{Q}_n^0(\gamma) + \mathbf{Q}_n^0(\gamma) - \mathbf{Q}_n^0(\gamma_0) + \mathbf{Q}_n^0(\gamma_0) - \mathbf{Q}_n(\gamma_0).$$

The result follows from

$$\sup_{\gamma \in \Theta_n(C)} |\mathbf{Q}_n(\gamma) - \mathbf{Q}_n^0(\gamma)| = o_p(1/h)$$

and

$$|\mathbf{Q}_n(\gamma_0) - \mathbf{Q}_n^0(\gamma_0)| = o_p(1/h),$$

together with Lemma 5.  $\square$

## Appendix C. Proofs of Theorems

### Proof of Theorem 1

*Proof.* The theorem follows directly from Lemma 1 and Lemma 6.  $\square$

### Proof of Theorem 2

*Proof.* Consider

$$\tilde{\mathbf{S}}_k(\boldsymbol{\gamma}) = \mathbb{E} \left\{ \frac{1}{n} \sum_{i=1}^n \mathbf{S}_{ik}(\boldsymbol{\gamma} + (nh)^{-1/2} \boldsymbol{\Omega}^{1/2} \boldsymbol{\delta}) \right\}.$$

Let  $\boldsymbol{\theta} = \sqrt{nh}(\boldsymbol{\gamma} - \boldsymbol{\gamma}_0)$ . By the Taylor expansion, for all  $\|\boldsymbol{\theta}\| \leq C$  with some finite constant  $C$ , we get

$$\sqrt{nh} \tilde{\mathbf{S}}_k(\boldsymbol{\gamma}_0 + \boldsymbol{\theta}/\sqrt{nh}) = \sqrt{nh} \tilde{\mathbf{S}}_k(\boldsymbol{\gamma}_0) + \tilde{\mathbf{S}}_k'(\boldsymbol{\gamma}_0) \boldsymbol{\theta} + o_p(1).$$

By (8) in Section 2.3, we get  $\tilde{\mathbf{S}}_k'(\boldsymbol{\gamma}_0) = -\frac{1}{n} \sum_i \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \boldsymbol{\Xi}_i \mathbf{U}_i$ , where  $\boldsymbol{\Xi}_i$  is an  $m_i \times m_i$  diagonal matrix with elements  $(\boldsymbol{\Xi}_i)_{jj} = \phi \left( \sqrt{nh} \frac{y_{ij} - \mathbf{U}_{ij}^T \boldsymbol{\gamma}_0}{r_{ij}} \right) \frac{\sqrt{nh}}{r_{ij}}$ . Denote  $a_{ij} = \mathbf{U}_{ij}^T \boldsymbol{\gamma}_0 - \mu_{ij}^0$ , then  $(\boldsymbol{\Xi}_i)_{jj} = \phi \left( \sqrt{nh} \frac{\epsilon_{ij} - a_{ij}}{r_{ij}} \right) \frac{\sqrt{nh}}{r_{ij}}$ . Furthermore, through calculating the expectation and variance of the each element of  $\tilde{\mathbf{S}}_k'(\boldsymbol{\gamma}_0)$ , we obtain

$$\tilde{\mathbf{S}}_k'(\boldsymbol{\gamma}_0) = -\frac{1}{n} \sum_i \mathbf{U}_i^T \boldsymbol{\Gamma}_i \mathbf{M}_{ki} \boldsymbol{\Lambda}_i \mathbf{U}_i + o_p(1), \quad (\text{S.13})$$

where  $\boldsymbol{\Lambda}_i$  is an  $m_i \times m_i$  diagonal matrix with elements  $\mathbb{E}_{\epsilon_{ij}} \phi \left( \sqrt{nh} \frac{\epsilon_{ij} - a_{ij}}{r_{ij}} \right) \frac{\sqrt{nh}}{r_{ij}}$ .

Note that

$$\begin{aligned} \mathbb{E}_{\epsilon_{ij}} \phi \left( \sqrt{nh} \frac{\epsilon_{ij} - a_{ij}}{r_{ij}} \right) \frac{\sqrt{nh}}{r_{ij}} &= \int \frac{\sqrt{nh}}{r_{ij}} \phi \left( \sqrt{nh} \frac{t - a_{ij}}{r_{ij}} \right) f_{ij}(t) dt \\ &= \int \phi(t) f_{ij} \left( \frac{r_{ij}}{\sqrt{nh}} t + a_{ij} \right) dt \\ &= \int \phi(t) f_{ij}(0) dt + \frac{r_{ij}}{\sqrt{nh}} \int \phi(t) f_{ij}'(o^*) \left( t + \frac{\sqrt{nh}}{r_{ij}} a_{ij} \right) dt, \end{aligned}$$

where  $o^*$  lies between 0 and  $\frac{r_{ij}}{\sqrt{nh}} t + a_{ij}$ . Since  $a_{ij} = O_p(h^r)$  and  $r_{ij} = O_p(\|\mathbf{U}_{ij}\|) = O_p(h^{-1/2})$ , by Condition (C2),

$$\left| \frac{r_{ij}}{\sqrt{nh}} \int \phi(t) f_{ij}'(o^*) \left( t + \frac{\sqrt{nh}}{r_{ij}} a_{ij} \right) dt \right| = O_p \left( \frac{r_{ij}}{\sqrt{nh}} \int |t| \phi(t) dt + a_{ij} \right) \rightarrow 0$$

as  $n \rightarrow \infty$ . Therefore, we obtain  $E_{\epsilon_{ij}} \phi \left( \sqrt{nh} \frac{\epsilon_{ij} - a_{ij}}{r_{ij}} \right) \frac{\sqrt{nh}}{r_{ij}} = f_{ij}(0) + o_p(1)$ .

Denote  $\mathbf{G}_k = \frac{1}{n} \sum_i \mathbf{U}_i^T \mathbf{\Gamma}_i \mathbf{M}_{ki} \mathbf{\Gamma}_i \mathbf{U}_i$  and  $\mathbf{G} = (\mathbf{G}_1^T, \dots, \mathbf{G}_v^T)^T$ . Then, we have

$$\sqrt{nh} \tilde{\mathbf{S}}(\boldsymbol{\gamma}_0 + \boldsymbol{\theta} / \sqrt{nh}) = \sqrt{nh} \tilde{\mathbf{S}}(\boldsymbol{\gamma}_0) - \mathbf{G} \boldsymbol{\theta} + o_p(1). \quad (\text{S.14})$$

On the other hand, it is not difficult to see from the previous proofs for the unsmoothed case that

$$\sqrt{nh} \mathbf{S}(\boldsymbol{\gamma}_0 + \boldsymbol{\theta} / \sqrt{nh}) = \sqrt{nh} \mathbf{S}(\boldsymbol{\gamma}_0) - \mathbf{G} \boldsymbol{\theta} + o_p(1). \quad (\text{S.15})$$

Therefore, if the following equation

$$\sqrt{nh} \|\tilde{\mathbf{S}}(\boldsymbol{\gamma}_0) - \mathbf{S}(\boldsymbol{\gamma}_0)\|_2 \rightarrow 0 \quad (\text{S.16})$$

holds in probability, then by (S.14) and (S.15), we have

$$\sup_{\|\boldsymbol{\gamma} - \boldsymbol{\gamma}_0\|_2 \leq C/\sqrt{nh}} \|\tilde{\mathbf{S}}(\boldsymbol{\gamma}) - \mathbf{S}(\boldsymbol{\gamma})\|_2 = o_p(1/\sqrt{nh})$$

for given  $C$ . And, by the similar proof line of Lemma 4, we can get

$$\sup_{\|\boldsymbol{\gamma} - \boldsymbol{\gamma}_0\|_2 \leq C/\sqrt{nh}} \|\tilde{\mathbf{Q}}(\boldsymbol{\gamma}) - \mathbf{Q}(\boldsymbol{\gamma})\|_2 = o_p(1/h).$$

Similar to the proof of Lemma 5, Lemma 6 and Theorem 1, we can obtain the desired result.

The proof of (S.16) can be done directly by calculating its expectation and variance and we omit it here.  $\square$

### Proof of Theorem 3

*Proof.* Let  $L_n(\boldsymbol{\gamma}) = \mathbf{Q}_n(\boldsymbol{\gamma}) + n \sum_{l=1}^p p_{\lambda_l}(\|\boldsymbol{\gamma}_l\|_{\mathbf{H}_l})$ . We next prove that for large  $n$  and any  $\varepsilon > 0$ , there exists a constant  $C$  large enough such that

$$P \left( \inf_{\boldsymbol{\gamma}: \|\mathbf{B}^T(\boldsymbol{\gamma} - \boldsymbol{\gamma}_0)\|_2 = C/\sqrt{nh}} L_n(\boldsymbol{\gamma}) > L_n(\boldsymbol{\gamma}_0) \right) \geq 1 - \varepsilon. \quad (\text{S.17})$$

As a result, (S.17) implies that  $L_n(\cdot)$  has a local minimum in the ball  $\{\boldsymbol{\gamma} : \|\mathbf{B}^T(\boldsymbol{\gamma} - \boldsymbol{\gamma}_0)\|_2 = C/\sqrt{nh}\}$ , which will imply the desired result.



To prove (S.17), using  $p_{\lambda_l}(0) = 0$  and  $p_{\lambda_l}(0) \geq 0$ , we have

$$L_n(\boldsymbol{\gamma}) - L_n(\boldsymbol{\gamma}_0) \geq \mathbf{Q}_n(\boldsymbol{\gamma}) - \mathbf{Q}_n(\boldsymbol{\gamma}_0) + n \sum_{l=1}^{d_0} \{p_{\lambda_l}(\|\boldsymbol{\gamma}_l\|_{\mathbf{H}_l}) - p_{\lambda_l}(\|\boldsymbol{\gamma}_l^0\|_{\mathbf{H}_l})\}. \quad (\text{S.18})$$

It is easy to see that for any  $\boldsymbol{\gamma}$  satisfying  $\|\mathbf{B}^T(\boldsymbol{\gamma} - \boldsymbol{\gamma}_0)\|_2 = O_p(1/\sqrt{nh})$ , both  $\|\boldsymbol{\gamma}_l\|_{\mathbf{H}_l} \geq a\lambda_l$  and  $\|\boldsymbol{\gamma}_l^0\|_{\mathbf{H}_l} \geq a\lambda_l$  hold when  $n$  is sufficiently large if  $\lambda_l \rightarrow 0$ . Hence, by the property of the SCAD penalty function, we have

$$\sum_{l=1}^{d_0} \{p_{\lambda_l}(\|\boldsymbol{\gamma}_l\|_{\mathbf{H}_l}) - p_{\lambda_l}(\|\boldsymbol{\gamma}_l^0\|_{\mathbf{H}_l})\} = 0 \quad (\text{S.19})$$

when  $n$  is sufficiently large.

By Lemma 6, on the set  $\Theta = \{\boldsymbol{\gamma} : \|\mathbf{B}^T(\boldsymbol{\gamma} - \boldsymbol{\gamma}_0)\|_2 = C/\sqrt{nh}\}$ , we have

$$P(\inf_{\boldsymbol{\gamma} \in \Theta} \mathbf{Q}_n(\boldsymbol{\gamma}) - \mathbf{Q}_n(\boldsymbol{\gamma}_0) > 0) > 1 - \varepsilon \quad (\text{S.20})$$

for any small  $\varepsilon > 0$  when  $n$  is sufficiently large, which implies (S.17). □

#### Proof of Theorem 4

*Proof.* We prove the sparsity by contradiction. Suppose that there exists a  $(d_0 + 1) \leq l \leq p$  such that  $\hat{\alpha}_l^P \neq 0$ . Let  $\boldsymbol{\gamma}^*$  be the vector obtained from  $\hat{\boldsymbol{\gamma}}^P$  with  $l$ -th component  $\hat{\boldsymbol{\gamma}}_l^P$  being replaced by 0. It will be shown that

$$L_n(\hat{\boldsymbol{\gamma}}^P) > L_n(\boldsymbol{\gamma}^*), \quad (\text{S.21})$$

which is a contradiction.

Note that

$$L_n(\hat{\boldsymbol{\gamma}}^P) - L_n(\boldsymbol{\gamma}^*) = \mathbf{Q}_n(\hat{\boldsymbol{\gamma}}^P) - \mathbf{Q}_n(\boldsymbol{\gamma}^*) + np_{\lambda_l}(\|\hat{\boldsymbol{\gamma}}_l^P\|_{\mathbf{H}_l}). \quad (\text{S.22})$$

For the penalty term  $np_{\lambda_l}(\|\hat{\boldsymbol{\gamma}}_l^P\|_{\mathbf{H}_l})$  in (S.22), since  $\|\hat{\boldsymbol{\gamma}}_l^P\|_{\mathbf{H}_l} = O_p(1/\sqrt{nh}) = o(\lambda_l)$ , by the expression of the SCAD penalty, we have

$$np_{\lambda_l}(\|\hat{\boldsymbol{\gamma}}_l^P\|_{\mathbf{H}_l}) = n\lambda_l\|\hat{\boldsymbol{\gamma}}_l^P\|_{\mathbf{H}_l},$$

with probability approaching 1.

For  $\mathbf{Q}_n(\hat{\boldsymbol{\gamma}}^P) - \mathbf{Q}_n(\boldsymbol{\gamma}^*)$ , by the similar expansion used in Lemmas 4-6, we can prove

$$\begin{aligned} |\mathbf{Q}_n(\hat{\boldsymbol{\gamma}}^P) - \mathbf{Q}_n(\boldsymbol{\gamma}^*)| &= O_p\left(\sqrt{\frac{n}{h}}\|\hat{\boldsymbol{\gamma}}^P - \boldsymbol{\gamma}^*\|_2\right) \\ &= O_p\left(\sqrt{\frac{n}{h}}\|\hat{\boldsymbol{\gamma}}_l^P\|_{\mathbf{H}_l}\right). \end{aligned}$$

Since  $\min_l \lambda_l n^{r/(2r+1)} \rightarrow \infty$ , the penalty term is the dominant term in (S.22), and (S.22) is positive with probability approaching 1, which is a contradiction.  $\square$

## Appendix D. Some Tables

### References

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Table 1: Mean and standard deviation of AIMSE ( $\times 100$ ) with SCAD penalty for divergent dimension  $p = \lceil n^{1/2} \rceil$  in Example 2 .

Model	Error	$\tau$	Penalized estimate			Oracle estimate		
			WI	QIF-CS	QIF-AR	WI	QIF-CS	QIF-AR
HM	Normal-CS	0.25	3.7683	3.4452	3.6053	3.3133	1.6467	2.1449
			2.0124	1.5938	2.1150	1.7800	0.8398	1.0814
		0.5	3.2106	2.3316	2.9449	2.9836	1.3332	1.7782
			1.6352	1.1282	1.4577	1.6389	0.5786	0.8623
	Normal-AR	0.25	4.3749	4.3208	4.2865	3.4143	3.2041	2.4425
			2.0746	2.5094	2.1002	1.4687	1.3536	1.0164
		0.5	3.8609	3.8437	3.8255	3.0331	2.6918	2.2028
			1.8659	2.5699	1.9876	1.3823	1.1313	1.0951
	t-CS	0.25	5.9815	5.0874	5.7861	5.5239	2.7862	3.4634
			3.1152	2.5283	3.3309	3.0939	1.6518	1.7747
		0.5	3.7140	2.5541	3.1955	3.3510	1.5983	2.0209
			1.8262	1.1476	1.6550	1.6078	0.7857	0.9673
t-AR	0.25	6.4317	6.1757	5.9001	5.4388	4.8993	4.0250	
		3.2455	3.5592	3.2448	2.6951	2.6941	1.9092	
	0.5	4.5197	4.4046	4.3651	3.4973	3.0396	2.3898	
		2.3046	3.1533	2.0071	1.7136	1.6474	1.1354	
HT	Normal-CS	0.25	9.1378	7.3080	9.0360	6.7065	4.0029	5.3356
			4.5228	3.3541	4.4581	3.1707	1.9201	3.0351
		0.5	7.6052	5.3813	7.2759	6.1978	3.1219	4.2959
			3.6879	2.4015	3.6149	3.2437	1.3238	1.8428
	Normal-AR	0.25	11.1713	10.3638	10.2541	7.5311	7.3759	6.2250
			4.7264	5.2473	5.0741	3.0786	3.0901	2.6846
		0.5	8.9280	8.8312	8.6933	6.7230	6.0828	5.3273
			4.3854	4.8328	3.9472	2.9976	2.4674	2.5820
	t-CS	0.25	18.1109	11.2549	16.2405	11.3302	6.6377	8.3862
			9.3907	5.2600	8.2955	5.6889	3.7501	4.3779
		0.5	8.8348	7.0418	8.0592	7.0082	3.7593	5.0501
			4.3352	3.2325	4.7830	3.2100	1.8540	2.3530
t-AR	0.25	18.0460	17.1934	17.0211	12.0352	11.2474	9.9787	
		8.3855	9.6504	8.3061	5.4686	6.5977	4.6405	
	0.5	10.2997	10.0843	9.4915	7.5855	7.1556	6.0257	
		4.9041	5.2676	4.5249	3.4021	3.9304	3.0565	

Table 2: Variable selection results for Example 2 with divergent dimension  $p = [n^{1/2}]$ .

Model	Error	$\tau$	FNR			FPR		
			WI	QIF-CS	QIF-AR	WI	QIF-CS	QIF-AR
HM	Normal-CS	0.25	0	0	0	0.040	0.038	0.039
		0.5	0	0	0	0.026	0.023	0.026
	Normal-AR	0.25	0	0	0	0.042	0.039	0.040
		0.5	0	0	0	0.028	0.027	0.027
	t-CS	0.25	0	0	0	0.060	0.055	0.058
		0.5	0	0	0	0.041	0.039	0.040
	t-AR	0.25	0	0	0	0.076	0.075	0.077
		0.5	0	0	0	0.050	0.045	0.047
HT	Normal-CS	0.25	0	0	0	0.104	0.101	0.107
		0.5	0	0	0	0.091	0.089	0.091
	Normal-AR	0.25	0	0	0	0.124	0.121	0.127
		0.5	0	0	0	0.100	0.095	0.099
	t-CS	0.25	0	0.001	0.001	0.183	0.182	0.187
		0.5	0	0	0	0.114	0.110	0.115
	t-AR	0.25	0	0.002	0.002	0.193	0.192	0.193
		0.5	0	0	0	0.124	0.123	0.125