

## Supplementary material for “Inference for dependent error functional data with application to event related potentials ”

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This supplement contains all the proofs for the main results.

### S.1 Preliminaries

Throughout this section,  $\mathcal{O}_p$  (or  $\mathcal{o}_p$ ) denotes a sequence of random variables of certain order in probability. For instance,  $\mathcal{o}_p(n^{-1/2})$  means a smaller order than  $n^{-1/2}$  in probability, and by  $\mathcal{O}_{a.s.}$  (or  $\mathcal{o}_{a.s.}$ ) almost surely  $\mathcal{O}$  (or  $\mathcal{o}$ ). In addition,  $\mathcal{U}_p$  denotes a sequence of random functions which are  $\mathcal{O}_p$  uniformly defined in the domain.

For any vector  $\mathbf{a} = (a_1, \dots, a_n) \in \mathbb{R}^n$ , denote the norm  $\|\mathbf{a}\|_r = (|a_1|^r + \dots + |a_n|^r)^{1/r}$ ,  $1 \leq r < +\infty$ ,  $\|\mathbf{a}\|_\infty = \max(|a_1|, \dots, |a_n|)$ . For any matrix  $\mathbf{A} = (a_{ij})_{i=1, j=1}^{m, n}$ , denote its  $L_r$  norm as  $\|\mathbf{A}\|_r = \max_{\mathbf{a} \in \mathbb{R}^n \setminus \{0\}} \|\mathbf{A}\mathbf{a}\|_r / \|\mathbf{a}\|_r$ , for  $r < +\infty$  and  $\|\mathbf{A}\|_\infty = \max_{1 \leq i \leq m} \sum_{j=1}^n |a_{ij}|$ . we will introduce the following lemmas needed in the proofs of the main results.

**Lemma S.1** (*Theorem 2.6.7, Csörgő and Révész (1981)*) *Suppose that  $\{\xi_i\}_{i \in \mathbb{N}_+}$  are i.i.d. on a probability space  $(\Omega, \mathcal{A}, \mathbb{P})$ , with  $\mathbb{E}(\xi_1) = 0$ ,  $\mathbb{E}(\xi_1^2) = 1$  and  $H(x) > 0$  ( $x \geq 0$ ) is an increasing continuous function such that  $x^{-2-\gamma}H(x)$  is increasing for some  $\gamma > 0$  and  $x^{-1} \log H(x)$  is decreasing with  $\mathbb{E}H(|\xi_1|) < \infty$ . Then there exist random variables  $\{\tilde{\xi}_i\}_{i \in \mathbb{N}_+}$  and a Wiener process  $W(t), t \in [0, +\infty)$  on a new probability space  $(\tilde{\Omega}, \tilde{\mathcal{A}}, \tilde{\mathbb{P}})$  such that  $\{\tilde{\xi}_i\}_{i \in \mathbb{N}_+} \stackrel{D}{=} \{\xi_i\}_{i \in \mathbb{N}_+}$ , and constants  $C_1, C_2, a > 0$  depending only on the distribution of  $\xi_1$ , such that  $\tilde{\mathbb{P}} \left\{ \max_{1 \leq m \leq n} \left| \tilde{S}_m - W(m) \right| > x_n \right\} \leq C_2 n \{H(ax_n)\}^{-1}$ ,  $n \in \mathbb{N}_+$  for any  $\{x_n\}_{n=1}^\infty$  satisfying  $H^{-1}(n) < x_n < C_1 (n \log n)^{1/2}$ , and  $\tilde{S}_m = \sum_{i=1}^m \tilde{\xi}_i$  for any  $m \in \mathbb{N}_+$ .*

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**Lemma S.2** *Let  $W_i \sim N(0, \sigma_i^2)$ ,  $\sigma_i > 0$ ,  $i = 1, \dots, n$ , then for  $n > 2$ ,  $a > 2$*

$$\mathbb{P}\left(\max_{1 \leq i \leq n} |W_i/\sigma_i| > a\sqrt{\log n}\right) < \sqrt{\frac{2}{\pi}} n^{1-a^2/2}. \quad (\text{S.1})$$

*Hence,  $(\max_{1 \leq i \leq n} |W_i|) / (\max_{1 \leq i \leq n} \sigma_i) \leq \max_{1 \leq i \leq n} |W_i/\sigma_i| = \mathcal{O}_{a.s.}(\sqrt{\log n})$ .*

PROOF. Note that

$$\begin{aligned} \mathbb{P}\left(\max_{1 \leq i \leq n} \left|\frac{W_i}{\sigma_i}\right| > a\sqrt{\log n}\right) &\leq \sum_{i=1}^n \mathbb{P}\left(\left|\frac{W_i}{\sigma_i}\right| > a\sqrt{\log n}\right) \\ &\leq 2n \left\{1 - \Phi\left(a\sqrt{\log n}\right)\right\} < 2n \frac{\phi\left(a\sqrt{\log n}\right)}{a\sqrt{\log n}} \\ &\leq 2n\phi\left(a\sqrt{\log n}\right) = \sqrt{\frac{2}{\pi}} n^{1-a^2/2}, \end{aligned}$$

for  $n > 2$ ,  $a > 2$ , which proves (S.1). The lemma follows by applying Borel-Cantelli Lemma with choice of  $a > 2$ .

**Lemma S.3** *The inequalities in (7), (8), (9), (10) are consistent and ensure that there exists  $\gamma$  which satisfies (11). Under Assumptions (A3), (A6), as  $n \rightarrow \infty$ ,*

$$J_s^{-p^*} (n \log n)^{2/r_0} = o(n^{-1/2}), \quad (\text{S.2})$$

$$N J_s^{-1} N^{-\nu} = o(1), \quad (\text{S.3})$$

$$N^{-1/2} J_s^{1/2} \sqrt{\log N} = o(N^{-\beta_2/2 - \theta/4}) = o(1), \quad (\text{S.4})$$

$$N^{\beta_2 - 1} J_s = o(n^{-1/2}). \quad (\text{S.5})$$

PROOF. Note first that (7) merely specifies appropriate range for Hölder continuity indices  $\mu$  and  $\nu$ . Next, since (8) requires that  $\theta < 2\nu$ ,  $\theta < 2p^*/(1+p^*)$ , it follows that  $\nu - \theta/2 > 0$ ,  $1 - \theta/2 - \theta/2p^* > 0$  and thus there exists  $\beta_2$  that satisfies (9).

Since (9) compels  $\beta_2 < 1 - \theta/2 - \theta/2p^*$  hence  $1 - \beta_2 - \theta/2 > \theta/2p^*$ , so

$$2p^*(1 - \beta_2 - \theta/2) - \theta > 0 \quad (\text{S.6})$$

and  $r_0$  exists.

Now  $1 - \nu < 1 - \beta_2 - \theta/2$  follows from  $\beta_2 < \nu - \theta/2$  in (9), and  $\theta(1 + 4/r_0)/2p^* < 1 - \beta_2 - \theta/2$  follows from (10) and (S.6), thus

$$\max\{1 - \nu, \theta(1 + 4/r_0)/2p^*\} < 1 - \beta_2 - \theta/2,$$

so there exists  $\gamma$  that satisfies (11).

Note next that Assumptions (A3), (A6) imply that

$$J_s^{-p^*} (n \log n)^{2/r_0} n^{1/2} = \mathcal{O}\left(N^{-p^*\gamma} d_N^{-p^*} N^{\theta/2+2\theta/r_0} (\log n)^{2/r_0}\right) = \mathcal{O}\left(N^{\theta/2+2\theta/r_0-p^*\gamma} d_N^{-p^*} (\log n)^{2/r_0}\right),$$

since  $\theta/2+2\theta/r_0-p^*\gamma < 0$  according to (11), and  $d_N^{-p^*} = \mathcal{O}(\log^{\tau p^*} N)$ , so  $J_s^{-p^*} (n \log n)^{2/r_0} n^{1/2} = o(1)$ , proving (S.2).

Since  $J_s = N^\gamma d_N$ , one computes

$$\begin{aligned} N J_s^{-1} N^{-\nu} &= N^{1-\gamma-\nu} d_N^{-1} = \mathcal{O}(N^{1-\gamma-\nu} \log N), \\ N^{-1/2} J_s^{1/2} \sqrt{\log N} &= N^{(\gamma-1)/2} d_N^{\gamma/2} \sqrt{\log N} = \mathcal{O}\left(N^{(\gamma-1)/2} \log^{(\gamma+1)/2} N\right), \\ N^{\beta_2-1} J_s n^{1/2} &= \mathcal{O}(N^{\beta_2-1+\gamma+\theta/2} d_N) = \mathcal{O}(N^{\beta_2-1+\gamma+\theta/2} \log N), \end{aligned}$$

which are  $o(1)$  according to (11) and Equation (S.3)-(S.5) hold.

In the following, the discrepancy  $\widehat{m}(\cdot) - \overline{m}(\cdot)$  is decomposed into simpler parts, to provides insights on how the B-spline estimator's bias and variance are reduced to order  $o_{a.s.}(n^{-1/2})$  separately.

For any function  $\phi$  defined on  $[0, 1]$  denote  $\boldsymbol{\phi} = \{\phi(1/N), \dots, \phi(N/N)\}^\top$ , in particular,  $\boldsymbol{\eta}_i = \{\eta_i(1/N), \dots, \eta_i(N/N)\}^\top$ ,  $\mathbf{m} = \{m(1/N), \dots, m(N/N)\}^\top$ ,  $\mathbf{Z}_i = \{Z_i(1/N), \dots, Z_i(N/N)\}^\top$ . In addition, denote by  $\mathbf{Y}_i = (Y_{i1}, \dots, Y_{iN})^\top$ ,  $\boldsymbol{\varepsilon}_i = (\sigma_i(1/N) \varepsilon_{i1}, \dots, \sigma_i(N/N) \varepsilon_{iN})^\top$  the response and error vectors of the  $i$ -th subject.

According to model (1) and (2),  $\mathbf{Y}_i = \boldsymbol{\eta}_i + \boldsymbol{\varepsilon}_i$ ,  $\boldsymbol{\eta}_i = \mathbf{m} + \mathbf{Z}_i$ . The design matrix for B-spline regression is

$$\mathbf{B} = \{\mathbf{B}(1/N), \dots, \mathbf{B}(N/N)\}^\top = \begin{pmatrix} B_{1,p}(1/N) & \cdots & B_{J_s+p,p}(1/N) \\ \vdots & \cdots & \vdots \\ B_{1,p}(N/N) & \cdots & B_{J_s+p,p}(N/N) \end{pmatrix}, \quad (\text{S.7})$$

where  $\mathbf{B}(x) = \{B_{1,p}(x), \dots, B_{J_s+p,p}(x)\}^\top$ .

For any two  $L^2$  integrable functions  $\phi(\cdot)$  and  $\varphi(\cdot)$ , define their theoretical and empirical inner products as  $\langle \phi, \varphi \rangle = \int_{[0,1]} \phi(x) \varphi(x) dx$ , and  $\langle \phi, \varphi \rangle_N = N^{-1} \sum_{j=1}^N \phi(j/N) \varphi(j/N)$  respectively. Correspondingly, the theoretical and empirical norms are  $\|\phi\|_2^2 = \langle \phi, \phi \rangle$  and  $\|\phi\|_{2,N}^2 = \langle \phi, \phi \rangle_N$ . Denote by  $\mathbf{V}_{n,p}$  the empirical inner product matrix of B-spline basis  $\{B_{\ell,p}(x)\}_{\ell=1}^{J_s+p}$ , i.e.

$$\mathbf{V}_{n,p} = \{\langle B_{\ell,p}, B_{\ell',p} \rangle_N\}_{\ell, \ell'=1}^{J_s+p} = N^{-1} \mathbf{B}^\top \mathbf{B}. \quad (\text{S.8})$$

The spline estimator  $\widehat{\eta}_i(\cdot)$  allows representation  $\widehat{\eta}_i(\cdot) = \mathbf{B}(\cdot)^\top (\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top \mathbf{Y}_i$ . The approximation error  $\widehat{\eta}_i(\cdot) - \eta_i(\cdot)$  is decomposed as

$$\widehat{\eta}_i(\cdot) - \eta_i(\cdot) = \widetilde{\eta}_i(\cdot) - \eta_i(\cdot) + \widetilde{\varepsilon}_i(\cdot), \quad (\text{S.9})$$

where

$$\widetilde{\eta}_i(\cdot) = N^{-1} \mathbf{B}(\cdot)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top \boldsymbol{\eta}_i = \widetilde{m}(\cdot) + \widetilde{Z}_i(\cdot), \quad (\text{S.10})$$

$$\widetilde{m}(\cdot) = N^{-1} \mathbf{B}(\cdot)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top \mathbf{m}, \quad \widetilde{Z}_i(\cdot) = N^{-1} \mathbf{B}(\cdot)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top \mathbf{Z}_i, \quad (\text{S.11})$$

$$\widetilde{\varepsilon}_i(\cdot) = N^{-1} \mathbf{B}(\cdot)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top \boldsymbol{\varepsilon}_i, \quad (\text{S.12})$$

Consequently, the approximation error of  $\widehat{m}(\cdot) - \overline{m}(\cdot)$  can be decomposed as

$$\begin{aligned} \widehat{m}(\cdot) - \overline{m}(\cdot) &= n^{-1} \sum_{i=1}^n \{\widehat{\eta}_i(\cdot) - \eta_i(\cdot)\} \\ &= n^{-1} \sum_{i=1}^n \{\widetilde{\eta}_i(\cdot) - \eta_i(\cdot)\} + n^{-1} \sum_{i=1}^n \widetilde{\varepsilon}_i(\cdot). \end{aligned} \quad (\text{S.13})$$

**Lemma S.4** *Under Assumptions (A1)–(A6), as  $n \rightarrow \infty$ , one has*

$$\max_{1 \leq i \leq n} \|\tilde{\eta}_i - \eta_i\|_\infty = \mathcal{O}_{a.s.} \left\{ J_s^{-p^*} (n \log n)^{2/r_0} \right\} = o_{a.s.} (n^{-1/2}).$$

**PROOF** The infeasible trajectory  $\eta_i(x)$  is written as  $\eta_i(x) = m(x) + \sum_{k=1}^{\infty} \xi_{ik} \phi_k(x)$ . For  $k = 1, 2, \dots$ , denote  $\phi_k = (\phi_k(1/N), \dots, \phi_k(N/N))^\top$ , and let  $\tilde{\phi}_k(x) = N^{-1} \mathbf{B}(x)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top \phi_k$  be the B-spline smoothing of  $\phi_k(x)$ . The linearity of spline smoothing implies that

$$\tilde{\eta}_i(x) - \eta_i(x) = \tilde{m}(x) - m(x) + \sum_{k=1}^{\infty} \xi_{ik} \left\{ \tilde{\phi}_k(x) - \phi_k(x) \right\}.$$

Lemma A.4 in Cao et al (2012) assures there exists a constant  $C_{q,\mu} > 0$ , such that

$$\|\tilde{m} - m\|_\infty \leq C_{q,\mu} \|m\|_{q,\mu} J_s^{-p^*}, \quad (\text{S.14})$$

$$\|\tilde{\phi}_k - \phi_k\|_\infty \leq C_{q,\mu} \|\phi_k\|_{q,\mu} J_s^{-p^*}, \quad k \geq 1 \quad (\text{S.15})$$

Thus, with norm inequality, we have

$$\|\tilde{\eta}_i - \eta_i\|_\infty \leq \|\tilde{m} - m\|_\infty + \sum_{k=1}^{\infty} |\xi_{ik}| \|\tilde{\phi}_k - \phi_k\|_\infty \leq C_{q,\mu} W_i J_s^{-p^*}, \quad (\text{S.16})$$

where  $W_i = \|m\|_{q,\mu} + \sum_{k=1}^{\infty} |\xi_{ik}| \|\phi_k\|_{q,\mu}$ ,  $i = 1, \dots, n$ , are i.i.d. nonnegative random variables. According to assumption (A4) and (A5'),  $W_i^{r_0}$  has a finite absolute moment and we have

$$\mathbb{P} \left\{ \max_{1 \leq i \leq n} W_i > (n \log n)^{2/r_0} \right\} \leq n \frac{\mathbb{E} W_i^{r_0}}{(n \log n)^2} = \mathbb{E} W_i^{r_0} (n \log n)^{-2},$$

which implies

$$\sum_{n=1}^{\infty} \mathbb{P} \left\{ \max_{1 \leq i \leq n} W_i > (n \log n)^{2/r_0} \right\} \leq \mathbb{E} W_i^{r_0} \sum_{n=1}^{\infty} (n \log n)^{-2} < +\infty.$$

Thus, according to Borel Cantelli lemma,  $\max_{1 \leq i \leq n} W_i = \mathcal{O}_{a.s.} \left\{ (n \log n)^{2/r_0} \right\}$  which, together with (S.16) and (S.2), prove the lemma.

The next result bounds the truncated tails of the infinite moving average.

**Lemma S.5** *Under Assumption (A5'), as  $n \rightarrow \infty$*

$$\max_{1 \leq i \leq n} \max_{1 \leq j \leq N} \left| \sum_{t=t_N+1}^{\infty} a_{it} \zeta_{i,j-t} \right| = \mathcal{O}_{a.s.} (N^{-5}).$$

PROOF Given that  $|a_{it}| \leq a\rho^t$ , one has

$$\mathbb{E} \left| \sum_{t=t_N+1}^{\infty} a_{it} \zeta_{i,j-t} \right| \leq \sum_{t=t_N+1}^{\infty} |a_{it}| \mathbb{E} |\zeta_{i,j-t}| \leq \mathbb{E} |\zeta_{i1}| \sum_{t=t_N+1}^{\infty} |a_{it}| \leq C\rho^{t_N}.$$

The choice of  $t_N$  ensures that the right side of the above is  $\leq CN^{-10}$ . Thus

$$\mathbb{P} \left( \max_{1 \leq i \leq n} \max_{1 \leq j \leq N} \left| \sum_{t=t_N+1}^{\infty} a_{it} \zeta_{i,j-t} \right| \geq N^{-5} \right) \leq n \times N \times \frac{CN^{-10}}{N^{-5}} \leq CN^{-4+\theta} \leq CN^{-4+2\nu} \leq CN^{-2}$$

because  $\theta < 2\nu$  by (8) and  $\nu \leq 1$  by definition. Borel-Cantelli lemma then proves the lemma.

**Lemma S.6** *Assumptions (A3), (A5') imply Assumption (A5) and*

$$\mathbb{P} \left\{ \max_{1 \leq i \leq n} \max_{0 \leq t \leq t_N} \max_{1 \leq j \leq N} \left| \sum_{j'=1}^j \zeta_{i,j'-t} - \sum_{j'=1}^j U_{i,j'-t,\zeta} \right| > 2N^{*\beta_2} \right\} \leq C(N^*)^{-\gamma_2}.$$

PROOF. Under Assumption (A5'),  $\mathbb{E} |\xi_{ik}|^{r_1} < +\infty$ ,  $r_1 > 4 + 2\omega$ , with  $\omega$  in Assumption (A4), so there exists  $\beta_1 \in (0, 1/2)$ , such that  $r_1 > (2 + \omega)/\beta_1$ . Denote  $H(x) = x^{r_1}$ , then Lemma S.1 entails that for each  $1 \leq k < \infty$ , there exist constants  $c_{1k}$  and  $a_k$  depending on the distribution of  $\xi_{ik}$ , such that for  $x_n = n^{\beta_1}$ ,  $n/H(a_k x_n) = a_k^{-r_1} n^{1-r_1\beta_1}$  and i.i.d.  $N(0, 1)$  variables  $\{U_{ik,\xi}\}_{i=1}^n$  on new probability space  $(\tilde{\Omega}_{k,\xi}, \tilde{\mathcal{A}}_{k,\xi}, \tilde{\mathbb{P}}_{k,\xi})$

$$\tilde{\mathbb{P}}_{k,\xi} \left\{ \max_{1 \leq t \leq n} \left| \sum_{i=1}^t \tilde{\xi}_{ik} - \sum_{i=1}^t U_{ik,\xi} \right| > n^{\beta_1} \right\} < c_{1k} a_k^{-r_1} n^{1-r_1\beta_1},$$

where  $\{\tilde{\xi}_{ik}\}_{i=1}^n$  are defined on  $(\tilde{\Omega}_{k,\xi}, \tilde{\mathcal{A}}_{k,\xi}, \tilde{\mathbb{P}}_{k,\xi})$  and equal in distribution to  $\{\xi_{ik}\}_{i=1}^n$ . Likewise, under Assumption (A5'),  $\mathbb{E} |\zeta_{i,j}|^{r_2} < +\infty$ ,  $r_2 > 4 + 2\theta$ , where  $\theta$  is defined in Assumption (A3), so there exists some  $\beta_2 \in (0, 1/2)$ , such that  $r_2 > (2 + \theta)/\beta_2$ . For  $N^* = N + t_N$

given in Assumption (A5), and  $H(x) = x^{r_2}$ ,  $x_{N^*} = N^{*\beta_2}$ , it is easy to check that with  $j = 1 - t_N, \dots, N$  playing the role of  $i = 1, \dots, n$  the condition of Lemma S.1 is satisfied under Assumption (A5). Hence for each  $i \in \{1, \dots, n\}$ , according to Lemma S.1, there exist positive constants  $c_i$  and  $b_i$  depending on the distribution of  $\zeta_{i,j}$ , and i.i.d.  $N(0, 1)$  variables  $U_{i,j,\zeta}$  on new probability space  $(\tilde{\Omega}_{i,\zeta}, \tilde{\mathcal{A}}_{i,\zeta}, \tilde{\mathbb{P}}_{i,\zeta})$  such that

$$\tilde{\mathbb{P}}_{i,\zeta} \left\{ \max_{1-t_N \leq j \leq N} \left| \sum_{j'=1-t_N}^j \tilde{\zeta}_{i,j'} - \sum_{j'=1-t_N}^j U_{i,j',\zeta} \right| > x_{N^*} \right\} < c_i N^* / H(b_i x_{N^*}) \leq C_i N^{*1-r_2\beta_2},$$

where  $\{\tilde{\zeta}_{i,j'}\}_{1-t_N}^N$  are defined on  $(\tilde{\Omega}_{i,\zeta}, \tilde{\mathcal{A}}_{i,\zeta}, \tilde{\mathbb{P}}_{i,\zeta})$  and equal in distribution to  $\{\zeta_{i,j'}\}_{1-t_N}^N$ .

Since Assumption (A5') stipulates the independence of  $\{\xi_{ik}\}_{i=1,k=1}^{n,\infty}$  and  $\{\zeta_{i,j'}\}_{i=1,j'=1-t_N}^{n,N}$ , this independence is automatically preserved for  $\{\tilde{\xi}_{ik}\}_{i=1,k=1}^{n,\infty}$  and  $\{\tilde{\zeta}_{i,j'}\}_{i=1,j'=1-t_N}^{n,N}$  if their new probability spaces  $(\tilde{\Omega}_{k,\xi}, \tilde{\mathcal{A}}_{k,\xi}, \tilde{\mathbb{P}}_{k,\xi})$ ,  $k \geq 1$  and  $(\tilde{\Omega}_{i,\zeta}, \tilde{\mathcal{A}}_{i,\zeta}, \tilde{\mathbb{P}}_{i,\zeta})$ ,  $i \geq 1$  are all independently embedded into a product probability space

$$\begin{aligned} & (\tilde{\Omega}, \tilde{\mathcal{A}}, \tilde{\mathbb{P}}) \equiv \\ & \left( \left( \bigotimes_{k=1}^{\infty} \tilde{\Omega}_{k,\xi} \right) \otimes \left( \bigotimes_{i=1}^{\infty} \tilde{\Omega}_{i,\zeta} \right), \left( \bigotimes_{k=1}^{\infty} \tilde{\mathcal{A}}_{k,\xi} \right) \otimes \left( \bigotimes_{i=1}^{\infty} \tilde{\mathcal{A}}_{i,\zeta} \right), \tilde{\mathbb{P}} \right) \end{aligned}$$

according to Ionescu–Tulcea Theorem (Theorem 14.32 in Klenke 2014). This independent embedding also ensures that all  $N(0, 1)$  variables  $\{U_{ik,\xi}\}_{i=1,k=1}^{n,\infty}$   $\{U_{i,j,\zeta}\}_{i=1,j=1-t_N}^{n,N}$  remain independent in the new product probability space, hence  $\{U_{ik,\xi}\}_{i=1,k=1}^{n,\infty}$  and  $\{U_{i,j,\zeta}\}_{i=1,j=1-t_N}^{n,N}$  are i.i.d.  $N(0, 1)$  as required in Assumption (A5).

In what follows, with some abuse of notations, we will not distinguish  $\xi_{ik}, \zeta_{i,j}$  on the original probability space from  $\tilde{\xi}_{ik}, \tilde{\zeta}_{i,j}$  on the above product probability space, nor the original probability measure  $\mathbb{P}$  from  $\tilde{\mathbb{P}}$  on the product space.

As the number of distinct distributions for  $\xi_{ik}$  is finite, there is a common  $c > 0$ , such that  $\mathbb{P} \left\{ \max_{1 \leq t \leq n} \left| \sum_{i=1}^t \xi_{ik} - \sum_{i=1}^t U_{ik,\xi} \right| > n^{\beta_1} \right\} < cn^{1-r_1\beta_1}$ , for each  $1 \leq k < \infty$ . Consequently, there is a  $c_1 > 0$  such that

$$\mathbb{P} \left\{ \max_{1 \leq k \leq k_n} \max_{1 \leq t \leq n} \left| \sum_{i=1}^t \xi_{ik} - \sum_{i=1}^t U_{ik,\xi} \right| > n^{\beta_1} \right\} < k_n cn^{1-r_1\beta_1} \leq c_1 n^{-\gamma_1},$$

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where  $\gamma_1 = r_1\beta_1 - 1 - \omega > 1$  by noticing that  $r_1 > (2 + \omega) / \beta_1$ .

Since the number of distinct distributions for  $\{\zeta_{i,1}\}_{i \geq 1}$  is finite, there exists a constant  $c$  such that for all  $i \in \{1, \dots, n\}$

$$\mathbb{P} \left\{ \max_{1-t_N \leq j \leq N} \left| \sum_{j'=1-t_N}^j \zeta_{i,j'} - \sum_{j'=1-t_N}^j U_{i,j',\zeta} \right| > x_{N^*} \right\} < cN^{*1-r_2\beta_2}.$$

Thus

$$\mathbb{P} \left\{ \max_{1 \leq i \leq n} \max_{1-t_N \leq j \leq N} \left| \sum_{j'=1-t_N}^j \zeta_{i,j'} - \sum_{j'=1-t_N}^j U_{i,j',\zeta} \right| > x_{N^*} \right\} < cnN^{*1-r_2\beta_2} \leq c_2 (N^*)^{1-r_2\beta_2+\theta}$$

Let  $\gamma_2 = r_2\beta_2 - \theta - 1$ , Since  $r_2 > (2 + \theta) / \beta_2$  according to the above discussion, it is easy to see that  $\gamma_2 > 1$ , so the Assumption (A5) is proved.

Next for  $t = 0, \dots, t_N$

$$\begin{aligned} & \max_{1 \leq j \leq N} \left| \sum_{j'=1}^j \zeta_{i,j'} - \sum_{j'=1}^j U_{i,j'-t,\zeta} \right| = \\ & \max_{1 \leq j \leq N} \left| \left( \sum_{j'=1-t_N}^{j-t} \zeta_{i,j'} - \sum_{j'=1-t_N}^{j-t} U_{i,j',\zeta} \right) - \left( \sum_{j'=1-t_N}^{-t} \zeta_{i,j'} - \sum_{j'=1-t_N}^{-t} U_{i,j',\zeta} \right) \right| \\ & \leq \max_{1 \leq j \leq N} \left| \sum_{j'=1-t_N}^{j-t} \zeta_{i,j'} - \sum_{j'=1-t_N}^{j-t} U_{i,j',\zeta} \right| + \left| \sum_{j'=1-t_N}^{-t} \zeta_{i,j'} - \sum_{j'=1-t_N}^{-t} U_{i,j',\zeta} \right| \\ & \leq 2 \max_{1-t_N \leq j \leq N} \left| \sum_{j'=1-t_N}^j \zeta_{i,j'} - \sum_{j'=1-t_N}^j U_{i,j',\zeta} \right| \end{aligned}$$



Thus

$$\begin{aligned}
& \mathbb{P} \left\{ \max_{0 \leq t \leq t_N} \max_{1 \leq j \leq N} \left| \sum_{j'=1}^j \zeta_{i,j'-t} - \sum_{j'=1}^j U_{i,j'-t,\zeta} \right| > 2N^{*\beta_2} \right\} \\
& \leq \mathbb{P} \left\{ 2 \max_{1-t_N \leq j \leq N} \left| \sum_{j'=1-t_N}^j \zeta_{i,j'} - \sum_{j'=1-t_N}^j U_{i,j',\zeta} \right| > 2N^{*\beta_2} \right\} \\
& = \mathbb{P} \left\{ \max_{1-t_N \leq j \leq N} \left| \sum_{j'=1-t_N}^j \zeta_{i,j'} - \sum_{j'=1-t_N}^j U_{i,j',\zeta} \right| > N^{*\beta_2} \right\} \leq CN^{*(1-r_2\beta_2)}.
\end{aligned}$$

Bonferroni technique then leads to

$$\mathbb{P} \left\{ \max_{1 \leq i \leq n} \max_{0 \leq t \leq t_N} \max_{1 \leq j \leq N} \left| \sum_{j'=1}^j \zeta_{i,j'-t} - U_{i,j'-t,\zeta} \right| > 2N^{*\beta_2} \right\} \leq CnN^{*(1-r_2\beta_2)} \leq C(N^*)^{-\gamma_2}.$$

The lemma holds consequently.

**Lemma S.7** *Under Assumptions (A2), (A6), as  $n \rightarrow \infty$*

$$\begin{aligned}
& \max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) \zeta_{i,j-t} \right| \\
& = \mathcal{O}_{a.s} \left( N^{-1/2} J_s^{-1/2} \sqrt{\log N} \right) + \mathcal{O}_{a.s} \left( N^{\beta_2-1} \right),
\end{aligned} \tag{S.17}$$

$$\begin{aligned}
& \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma \left( \frac{j}{N} \right) \zeta_{i,j-t} \right| \\
& = \mathcal{O}_{a.s} \left( N^{-1/2} n^{-1/2} J_s^{-1/2} \sqrt{\log N} \right) + \mathcal{O}_{a.s} \left( N^{\beta_2-1} \right).
\end{aligned} \tag{S.18}$$

**PROOF**

$$\begin{aligned}
& \max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) \zeta_{i,j-t} \right| \\
& \leq \max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right| + \\
& \max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) (\zeta_{i,j-t} - U_{i,j-t,\zeta}) \right|.
\end{aligned}$$

Where  $U_{i,j,\zeta}$  is defined in Assumption (A5). For the first part of equality above,

$$\begin{aligned} & \mathbb{E} \left\{ N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right\}^2 = \\ & N^{-2} \sum_{j=1}^N B_{\ell,p}^2 \left( \frac{j}{N} \right) \sigma_i^2 \left( \frac{j}{N} \right) \mathbb{E} U_{i,j-t,\zeta}^2 \leq \frac{C}{NJ_s} \\ & \mathbb{P} \left\{ \frac{\max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right|}{\left[ \mathbb{E} \left\{ N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right\}^2 \right]^{1/2}} \geq 4\sqrt{\log N} \right\} \\ & \leq t_N n (J_s + p) \mathbb{P} \left\{ \frac{\left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right|}{\left[ \mathbb{E} \left\{ N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right\}^2 \right]^{1/2}} \geq 4\sqrt{\log N} \right\} \\ & \leq t_N n (J_s + p) \exp \left\{ \frac{-4^2 \log N}{2} \right\} \leq C t_N n (J_s + p) N^{-8} \leq C N^{-8+\theta+\gamma} \log N \leq C N^{-5}, \end{aligned}$$

because  $\theta < 2\nu$  by (8) and  $\nu \leq 1$  by definition, and  $\gamma < 1 - \beta_2 - \theta/2 < 1$  by (11). Thus Borel-Cantelli lemma entails that

$$\begin{aligned} & \max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right| \\ & = \mathcal{O}_{a.s.} \left( N^{-1/2} J_s^{-1/2} \sqrt{\log N} \right). \end{aligned}$$

The counterpart for averaging over  $i = 1, \dots, n$  is worked out as

$$\begin{aligned} & \mathbb{P} \left\{ \frac{\max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right|}{\left\{ \mathbb{E} \left\{ n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right\}^2 \right\}^{1/2}} \geq 4\sqrt{\log N} \right\} \\ & \leq (J_s + p) t_N \mathbb{P} \left\{ \frac{\left| n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right|}{\left\{ \mathbb{E} \left\{ n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right\}^2 \right\}^{1/2}} \geq 4\sqrt{\log N} \right\} \\ & \leq (J_s + p) t_N \exp \left\{ \frac{-4^2 \log N}{2} \right\} \leq C (J_s + p) N^{-8} \leq C N^{-7}, \end{aligned}$$

while

$$\begin{aligned} & \mathbb{E} \left\{ n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) U_{i,j-t,\zeta} \right\}^2 \\ & (nN)^{-2} \sum_{i=1}^n \sum_{j=1}^N B_{\ell,p}^2 \left( \frac{j}{N} \right) \sigma_i^2 \left( \frac{j}{N} \right) \mathbb{E} U_{i,j-t,\zeta}^2 \leq \frac{C}{nN J_s} \end{aligned}$$

Notice next that

$$\begin{aligned} & \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) (\zeta_{i,j-t} - U_{i,j-t,\zeta}) \\ &= \sum_{j=1}^{N-1} \left\{ B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) - B_{\ell,p} \left( \frac{j+1}{N} \right) \sigma_i \left( \frac{j+1}{N} \right) \right\} \sum_{j'=1}^j (\zeta_{i,j'-t} - U_{i,j'-t,\zeta}) \\ &+ B_{\ell,p}(1) \sigma_i(1) \sum_{j'=1}^N (\zeta_{i,j'-t} - U_{i,j'-t,\zeta}) \end{aligned}$$

While

$$\begin{aligned} & \left| \sum_{j=1}^{N-1} \left\{ B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) - B_{\ell,p} \left( \frac{j+1}{N} \right) \sigma_i \left( \frac{j+1}{N} \right) \right\} \sum_{j'=1}^j (\zeta_{i,j'-t} - U_{i,j'-t,\zeta}) \right| \\ & \leq \sum_{j=1}^{N-1} \left| B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) - B_{\ell,p} \left( \frac{j+1}{N} \right) \sigma_i \left( \frac{j+1}{N} \right) \right| \left| \sum_{j'=1}^j (\zeta_{i,j'-t} - U_{i,j'-t,\zeta}) \right| \\ & \leq CN J_s^{-1} (N^{-\nu} + J_s N^{-1}) \max_{1 \leq j \leq N} \left| \sum_{j'=1}^j (\zeta_{i,j'-t} - U_{i,j'-t,\zeta}) \right| \end{aligned}$$

Consequently, according to (S.3),

$$\begin{aligned} & \max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s + p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) (\zeta_{i,j-t} - U_{i,j-t,\zeta}) \right| \\ & \leq N^{-1} C (N J_s^{-1} N^{-\nu} + 1) \max_{0 \leq t \leq t_N} \max_{1 \leq i \leq n} \max_{1 \leq j \leq N} \left| \sum_{j'=1}^j (\zeta_{i,j'-t} - U_{i,j'-t,\zeta}) \right| \end{aligned}$$

According to Lemma S.3, the inequality above becomes

$$\leq CN^{-1} \max_{0 \leq t \leq t_N} \max_{1 \leq i \leq n} \max_{1 \leq j \leq N} \left| \sum_{j'=1}^j (\zeta_{i,j'-t} - U_{i,j'-t,\zeta}) \right| = \mathcal{O}_{a.s.} (N^{-1} N^{*\beta_2}) = \mathcal{O}_{a.s.} (N^{\beta_2-1})$$

Combine the results above, the lemma is proved.

**Lemma S.8** *Under Assumptions (A5) and (A6), as  $n \rightarrow \infty$*

$$\max_{1 \leq i \leq n} \|\tilde{\varepsilon}_i\|_\infty = \max_{1 \leq i \leq n} \sup_{x \in [0,1]} |\tilde{\varepsilon}_i(x)| = \mathcal{O}_{a.s.} \left( N^{-1/2} J_s^{1/2} \sqrt{\log N} + N^{\beta_2-1} J_s \right). \quad (\text{S.19})$$

$$\left\| n^{-1} \sum_{i=1}^n \tilde{\varepsilon}_i \right\|_\infty = \mathcal{O}_{a.s.} \left( N^{-1/2} n^{-1/2} J_s^{1/2} \sqrt{\log N} \right) + \mathcal{O}_{a.s.} \left( N^{\beta_2-1} J_s \right) = o_{a.s.} \left( n^{-1/2} \right). \quad (\text{S.20})$$

PROOF One first writes  $\tilde{\varepsilon}_i(x)$  as a finite sum and an infinite remainder

$$\tilde{\varepsilon}_i(x) = \sum_{t=0}^{\infty} a_{it} \tilde{\zeta}_{i,-t}(x) = Q_{1i}(x) + Q_{2i}(x),$$

in which

$$Q_{1i}(x) = \sum_{t=0}^{t_N} a_{it} \tilde{\zeta}_{i,-t}(x), \quad Q_{2i}(x) = \sum_{t=t_N+1}^{\infty} a_{it} \tilde{\zeta}_{i,-t}(x), \quad (\text{S.21})$$

with

$$\tilde{\zeta}_{i,-t}(x) = N^{-1} \mathbf{B}(x)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top \left( \sigma_i(j/N) \zeta_{i,j-t} \right)_{1 \leq j \leq N}^\top.$$

The average  $n^{-1} \sum_{i=1}^n \tilde{\varepsilon}_i(x)$  is likewise decomposed as

$$n^{-1} \sum_{i=1}^n \tilde{\varepsilon}_i(x) = Q_1(x) + Q_2(x),$$

where

$$Q_1(x) = n^{-1} \sum_{i=1}^n Q_{1i}(x), \quad Q_2(x) = n^{-1} \sum_{i=1}^n Q_{2i}(x),$$

with  $Q_{1i}(x), Q_{2i}(x)$  defined in (S.21). The terms  $Q_{2i}, Q_2, Q_{1i}, Q_1$  are then bounded separately.

To begin with, note that

$$\begin{aligned} |Q_{2i}(x)| &= \left| N^{-1} \mathbf{B}(x)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top \left( \sum_{t=t_N+1}^{\infty} a_{it} \left( \sigma_i(j/N) \zeta_{i,j-t} \right)_{1 \leq j \leq N}^\top \right) \right| \\ &\leq \left| \mathbf{B}(x)^\top \mathbf{V}_{n,p}^{-1} N^{-1} \mathbf{B}^\top \mathbf{1}_N \right| \|\sigma_i\|_\infty \max_{1 \leq i \leq n} \max_{1 \leq j \leq N} \left| \sum_{t=t_N+1}^{\infty} a_{it} \zeta_{i,j-t} \right|. \end{aligned}$$

According to Lemma A.3 in Cao et al (2012),  $|\mathbf{V}_{n,p}^{-1}|_{\infty} \leq M_p J_s$ . Since the B-spline basis  $\|\mathbf{B}(x)\|_{\infty} \leq 1$  so  $\|N^{-1}\mathbf{B}^{\top}\mathbf{1}_N\|_{\infty} \leq 1$ , and Lemma S.5 ensures that

$$\max_{1 \leq i \leq n} \max_{1 \leq j \leq N} \left| \sum_{t=t_N+1}^{\infty} a_{it} \zeta_{i,j-t} \right| = \mathcal{O}_{a.s.}(N^{-5})$$

one obtains that

$$\begin{aligned} \max_{1 \leq i \leq n} \|Q_{2i}\|_{\infty} &= \max_{1 \leq i \leq n} \sup_{x \in [0,1]} |Q_{2i}(x)| \leq \sup_{x \in [0,1]} \left| |\mathbf{B}(x)^{\top} \mathbf{V}_{n,p}^{-1}|_{\infty} (J_s + p) \right| \times \mathcal{O}_{a.s.}(N^{-5}) \\ &\leq |M_p J_s (J_s + p)| \times \mathcal{O}_{a.s.}(N^{-5}) = \mathcal{O}_{a.s.}(N^{-3}). \end{aligned} \quad (\text{S.22})$$

One obtains immediately from (S.22) that

$$\|Q_2\|_{\infty} = \left\| n^{-1} \sum_{i=1}^n Q_{2i} \right\|_{\infty} \leq \max_{1 \leq i \leq n} \|Q_{2i}\|_{\infty} = \mathcal{O}_{a.s.}(N^{-3}) = o_{a.s.}(n^{-1/2}).$$

Meanwhile

$$\begin{aligned} \max_{1 \leq i \leq n} \sup_{x \in [0,1]} |Q_{1i}(x)| &= \max_{1 \leq i \leq n} \sup_{x \in [0,1]} \left| \sum_{t=0}^{t_N} a_{it} N^{-1} \mathbf{B}(x)^{\top} \mathbf{V}_{n,p}^{-1} \mathbf{B}^{\top} (\sigma_i(j/N) \zeta_{i,j-t})_{1 \leq j \leq N}^{\top} \right| \\ &\leq \max_{1 \leq i \leq n} \sup_{x \in [0,1]} \left| \sum_{t=0}^{t_N} a \rho^{t-1} \mathbf{B}(x)^{\top} \left( \mathbf{V}_{n,p}^{-1} N^{-1} \mathbf{B}^{\top} (\sigma_i(j/N) \zeta_{i,j-t})_{1 \leq j \leq N}^{\top} \right) \right| \\ &\leq \max_{1 \leq i \leq n} \sum_{t=0}^{t_N} a \rho^{t-1} p \left\| \mathbf{V}_{n,p}^{-1} N^{-1} \mathbf{B}^{\top} (\sigma_i(j/N) \zeta_{i,j-t})_{1 \leq j \leq N}^{\top} \right\|_{\infty} \\ &\leq \max_{1 \leq i \leq n} \sum_{t=0}^{t_N} a \rho^{t-1} p |\mathbf{V}_{n,p}^{-1}|_{\infty} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) \zeta_{i,j-t} \right| \\ &\leq C J_s \max_{1 \leq i \leq n} \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) \zeta_{i,j-t} \right| \\ &= \mathcal{O}_{a.s.} \left( N^{-1/2} J_s^{1/2} \sqrt{\log N} \right) + \mathcal{O}_{a.s.} (N^{\beta_2-1} J_s) \end{aligned}$$

according to (S.17).

Likewise

$$\begin{aligned} \sup_{x \in [0,1]} |Q_1(x)| &= \sup_{x \in [0,1]} \left| n^{-1} \sum_{i=1}^n \sum_{t=0}^{t_N} a_{it} N^{-1} \mathbf{B}(x)^\top \mathbf{V}_{n,p}^{-1} \mathbf{B}^\top (\sigma_i(j/N) \zeta_{i,j-t})_{1 \leq j \leq N}^\top \right| \\ &\leq C J_s \max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) \zeta_{i,j-t} \right|. \end{aligned}$$

Applying (S.18) in Lemma S.7, one obtains that

$$\begin{aligned} &\max_{1 \leq \ell \leq J_s+p} \max_{0 \leq t \leq t_N} \left| n^{-1} \sum_{i=1}^n N^{-1} \sum_{j=1}^N B_{\ell,p} \left( \frac{j}{N} \right) \sigma_i \left( \frac{j}{N} \right) \zeta_{i,j-t} \right| \\ &= \mathcal{O}_{a.s.} \left( n^{-1/2} N^{-1/2} J_s^{-1/2} \sqrt{\log N} \right) + \mathcal{O}_{a.s.} (N^{\beta_2-1}) \end{aligned}$$

and together with (S.4) and (S.5),

$$\begin{aligned} &\sup_{x \in [0,1]} |Q_1(x)| \\ &= \mathcal{O}_{a.s.} \left( N^{-1/2} n^{-1/2} J_s^{1/2} \sqrt{\log N} \right) + \mathcal{O}_{a.s.} (N^{\beta_2-1} J_s) = o_{a.s.} (n^{-1/2}). \end{aligned}$$

The lemma is proved.

## S.2 Proof of Theorem 1

Following the decomposition Equation (S.13), it suffices to bound term  $n^{-1} \sum_{i=1}^n \{\widehat{\eta}_i(\cdot) - \eta_i(\cdot)\}$  and term  $n^{-1} \sum_{i=1}^n \widetilde{\varepsilon}_i(\cdot)$  separately. Lemma S.4 has shown that  $\max_{1 \leq i \leq n} \|\widetilde{\eta}_i - \eta_i\|_\infty = \mathcal{O}_{a.s.} \left\{ J_s^{-p^*} (n \log n)^{2/r_0} \right\} = o_{a.s.} (n^{-1/2})$ . On the other hand, Equation (S.20) shows that  $\sup_{x \in (0,1)} |n^{-1} \sum_{i=1}^n \widetilde{\varepsilon}_i(x)| = o_{a.s.} (n^{-1/2})$ . Putting results together, one obtains

$$\begin{aligned} \sup_{x \in [0,1]} n^{1/2} |\widehat{m}(x) - \overline{m}(x)| &\leq n^{1/2} \max_{1 \leq i \leq n} \|\widetilde{\eta}_i - \eta_i\|_\infty + n^{1/2} \sup_{x \in (0,1)} \left| n^{-1} \sum_{i=1}^n \widetilde{\varepsilon}_i(x) \right| \\ &= o_{a.s.} (1). \end{aligned}$$

### S.3 Proof of Theorem 2

Denote a random process  $\varsigma(x)$  as

$$\varsigma(x) = n^{1/2} G(x, x)^{-1/2} \sum_{k=1}^{\infty} \bar{U}_{.k, \xi} \phi_k(x),$$

where  $\bar{U}_{.k, \xi} = n^{-1} \sum_{i=1}^n U_{ik, \xi}$ , with i.i.d.  $N(0, 1)$  variables  $U_{ik, \xi}$ ,  $1 \leq i \leq n, 1 \leq k < \infty$  given in Assumption (A5). Consequently,  $n^{1/2} \bar{U}_{.k, \xi}$  are i.i.d.  $N(0, 1)$ ,  $1 \leq k < \infty$ , so  $\varsigma(x)$  is a standardized Gaussian process (i.e., mean zero, variance one) with covariance function  $\mathbb{E} \varsigma(x) \varsigma(x') = G(x, x)^{-1/2} G(x', x')^{-1/2} G(x, x')$ , for any  $x, x' \in [0, 1]$ , thus having the same distribution as  $\zeta(x)$ .

Notice that  $\bar{m}(x) - m(x) = \sum_{k=1}^{\infty} \bar{\xi}_{.k} \phi_k(x)$ , in which  $\bar{\xi}_{.k} = n^{-1} \sum_{i=1}^n \xi_{ik}$ . Thus, it suffices to show that

$$\begin{aligned} & \sup_{x \in [0, 1]} \left| n^{1/2} G(x, x)^{-1/2} (\bar{m}(x) - m(x)) - \varsigma(x) \right| \\ &= n^{1/2} \sup_{x \in [0, 1]} G(x, x)^{-1/2} \left| \sum_{k=1}^{\infty} (\bar{\xi}_{.k} - \bar{U}_{.k, \xi}) \phi_k(x) \right| = o_p(1), \end{aligned}$$

the theorem is then proved with the help of Slutsky's Theorem.

Since  $G(x, x)$  has a positive lower bound  $C_G > 0$  according to Assumption (A4), one obtains

$$n^{1/2} \sup_{x \in [0, 1]} G(x, x)^{-1/2} \left| \sum_{k=1}^{\infty} (\bar{\xi}_{.k} - \bar{U}_{.k, \xi}) \phi_k(x) \right| \leq C n^{1/2} \sup_{x \in [0, 1]} \left| \sum_{k=1}^{\infty} (\bar{\xi}_{.k} - \bar{U}_{.k, \xi}) \phi_k(x) \right|.$$

Next, using the truncation technique, the right hand side of the inequality can be decomposed into

$$n^{1/2} \sup_{x \in [0, 1]} \left| \sum_{k=1}^{\infty} (\bar{\xi}_{.k} - \bar{U}_{.k, \xi}) \phi_k(x) \right| \leq I_1 + I_2,$$

where

$$I_1 = n^{1/2} \sup_{x \in [0, 1]} \sum_{k=1}^{k_n} |\bar{\xi}_{.k} - \bar{U}_{.k, \xi}| |\phi_k(x)|,$$

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and

$$I_2 = n^{1/2} \sup_{x \in [0,1]} \sum_{k=k_n+1}^{\infty} |\bar{\xi}_{.k} - \bar{U}_{.k,\xi}| |\phi_k(x)|.$$

By Assumption (A5)'s strong approximation equation of  $\{\xi_{ik}\}$  and Borel-Cantelli lemma,  $\max_{1 \leq k \leq k_n} |\bar{\xi}_{.k} - \bar{U}_{.k,\xi}| = \mathcal{O}_{a.s.}(n^{\beta_1-1})$ . Thus,

$$I_1 \leq n^{1/2} \max_{1 \leq k \leq k_n} |\bar{\xi}_{.k} - \bar{U}_{.k,\xi}| \sup_{x \in [0,1]} \sum_{k=1}^{k_n} |\phi_k(x)|_{\infty} = \mathcal{O}_{a.s.}(n^{\beta_1-1/2}) = o_{a.s.}(1).$$

On the other hand

$$\begin{aligned} \mathbb{E}I_2 &\leq n^{1/2} \sup_{x \in [0,1]} \sum_{k=k_n+1}^{\infty} (\mathbb{E} |\bar{\xi}_{.k}| + \mathbb{E} |\bar{U}_{.k,\xi}|) |\phi_k(x)| \\ &\leq n^{1/2} \sup_{x \in [0,1]} \sum_{k=k_n+1}^{\infty} \left( (\mathbb{E} |\bar{\xi}_{.k}|^2)^{1/2} + (\mathbb{E} |\bar{U}_{.k,\xi}|^2)^{1/2} \right) |\phi_k(x)| \\ &= n^{1/2} \sup_{x \in [0,1]} \sum_{k=k_n+1}^{\infty} \left( (n^{-1})^{1/2} + (n^{-1})^{1/2} \right) |\phi_k(x)| \\ &\leq \sum_{k=k_n+1}^{\infty} \sup_{x \in [0,1]} |\phi_k(x)| = \sum_{k=k_n+1}^{\infty} \|\phi_k\|_{\infty} = o(1), \end{aligned}$$

which leads to  $I_2 = o_p(1)$ .

Combining results above, one obtains

$$\sup_{x \in [0,1]} \left| n^{1/2} G(x, x)^{-1/2} (\bar{m}(x) - m(x)) - \varsigma(x) \right| = o_p(1),$$

thus for any fixed  $x \in [0, 1]$

$$\left| n^{1/2} G(x, x)^{-1/2} (\bar{m}(x) - m(x)) - \varsigma(x) \right| = o_p(1).$$

Applying Slutsky's Theorem,

$$\begin{aligned} \sup_{x \in [0,1]} \left| n^{1/2} G(x, x)^{-1/2} (\bar{m}(x) - m(x)) \right| &\rightarrow \sup_{x \in [0,1]} |\varsigma(x)|, \\ n^{1/2} G(x, x)^{-1/2} (\bar{m}(x) - m(x)) &\rightarrow \varsigma(x), x \in [0, 1], \end{aligned}$$



in distribution.

Consequently, notice that

$$\begin{aligned} & n^{1/2}G(x, x)^{-1/2}(\widehat{m}(x) - m(x)) \\ &= n^{1/2}G(x, x)^{-1/2}(\widehat{m}(x) - \overline{m}(x)) + n^{1/2}G(x, x)^{-1/2}(\overline{m}(x) - m(x)), \end{aligned}$$

in which the first term of right hand side is uniformly  $o_{a.s.}(1)$  according to Theorem 1, thus Banach space valued Slutsky's Theorem (Theorem 2.3, Bosq (2000)) entails that  $n^{1/2}G(x, x)^{-1/2}(\widehat{m}(x) - m(x))$  converges weakly to the same stochastic process as  $n^{1/2}G(x, x)^{-1/2}(\overline{m}(x) - m(x))$ . Hence Continuous Mapping Theorem for Banach space valued random variables (equation (2.11), Bosq (2000)) implies that

$$\begin{aligned} \sup_{x \in [0,1]} \left| n^{1/2}G(x, x)^{-1/2}(\widehat{m}(x) - m(x)) \right| &\rightarrow \sup_{x \in [0,1]} |\varsigma(x)|, \\ n^{1/2}G(x, x)^{-1/2}(\widehat{m}(x) - m(x)) &\rightarrow \varsigma(x), x \in [0, 1]. \end{aligned}$$

The Theorem is thus proved.

## S.4 Proof of Proposition 1

Note that for  $(x, x') \in [0, 1]^2$

$$\overline{G}(x, x') = n^{-1} \sum_{i=1}^n C_i(x, x'), C_i(x, x') = \{\eta_i(x) - m(x)\} \{\eta_i(x') - m(x')\}, \quad (\text{S.23})$$

where  $\{C_i(\cdot, \cdot)\}_{i=1}^n$  is an i.i.d. sequence of  $\mathcal{C}[0, 1]^2$  random variables. By the strong law of large numbers for Banach space valued random sequence (Theorem 2.4, Bosq (2000)), their sample mean  $\overline{G}(\cdot, \cdot)$  converges almost surely in Banach space norm to its mean  $\mathbb{E}C_1(\cdot, \cdot) \equiv G(\cdot, \cdot)$ , thus (14) is proved. Similarly, one obtains that  $\|\overline{m} - m\|_\infty = o_{a.s.}(1)$  and consequently  $\|\widehat{m} - m\|_\infty = o_{a.s.}(1)$ .

Next, notice that

$$\left(\widehat{G} - \overline{G}\right)(x, x') = n^{-1} \sum_{i=1}^n \{I_{1i}(x) I_{2i}(x') + I_{1i}(x') I_{2i}(x) - I_{1i}(x) I_{1i}(x')\},$$

where

$$\begin{aligned}
I_{1i}(\cdot) &= \widehat{\eta}_i(\cdot) - \eta_i(\cdot) - \{\widehat{m}(\cdot) - m(\cdot)\} \\
I_{2i}(\cdot) &= \widehat{\eta}_i(\cdot) - \widehat{m}(\cdot) \\
&= \widehat{\eta}_i(\cdot) - \eta_i(\cdot) - \{\widehat{m}(\cdot) - m(\cdot)\} + \eta_i(\cdot) - m(\cdot).
\end{aligned}$$

Equation (S.9), Lemmas S.4 and S.8 and Equation (S.4) imply

$$\begin{aligned}
\max_i \|\widehat{\eta}_i - \eta_i\|_\infty &\leq \max_i \|\widetilde{\eta}_i(\cdot) - \eta_i(\cdot)\|_\infty + \max_i \|\widetilde{\varepsilon}_i\|_\infty \\
&= o_{a.s.}(n^{-1/2}) + \mathcal{O}_{a.s.}\left(N^{-1/2} J_s^{1/2} \sqrt{\log N} + N^{\beta_2-1} J_s\right) \\
&= o_{a.s.}(n^{-1/2}) + o_{a.s.}(N^{-\beta_2/2-\theta/4}) = o_{a.s.}(1), \tag{S.24}
\end{aligned}$$

which, together with  $\|\widehat{m} - m\|_\infty = o_{a.s.}(1)$ , entail that  $\left\|\widehat{G} - \overline{G}\right\|_\infty = o_{a.s.}(1)$ , that is, (15). Equations (14)-(15) and triangle inequality of  $\|\cdot\|_\infty$  lead to (16). The Proposition is thus proved.

## S.5 Proof of Corollary 1

Notice that

$$\begin{aligned}
&n^{1/2} \widehat{G}(x, x)^{-1/2} (\widehat{m}(x) - m(x)) \\
&= n^{1/2} G(x, x)^{-1/2} (\widehat{m}(x) - m(x)) + n^{1/2} \left( \widehat{G}(x, x)^{-1/2} - G(x, x)^{-1/2} \right) (\widehat{m}(x) - m(x)).
\end{aligned}$$

Since  $G(x, x)$  is uniformly bounded away from 0 by Assumption (A4), one obtains  $\sup_{x \in [0,1]} \left| \widehat{G}(x, x)^{-1/2} - G(x, x)^{-1/2} \right| = o_{a.s.}(1)$  by (16). Meanwhile, Theorem 2 has shown that  $n^{1/2} (\widehat{m}(x) - m(x)) \rightarrow G^{1/2}(x, x) \zeta(x)$  in distribution and thus

$$\begin{aligned}
& \sup_{x \in [0,1]} n^{1/2} \left| \left( \widehat{G}(x, x)^{-1/2} - G(x, x)^{-1/2} \right) (\widehat{m}(x) - m(x)) \right| \\
& \leq \sup_{x \in [0,1]} \left| \widehat{G}(x, x)^{-1/2} - G(x, x)^{-1/2} \right| \sup_{x \in [0,1]} n^{1/2} |\widehat{m}(x) - m(x)| \\
& \xrightarrow{d} 0 \times \sup_{x \in [0,1]} |G^{1/2}(x, x) \zeta(x)|,
\end{aligned}$$

which leads to

$$n^{1/2} \left( \widehat{G}(x, x)^{-1/2} - G(x, x)^{-1/2} \right) (\widehat{m}(x) - m(x)) \rightarrow 0$$

in distribution as a Banach space valued random sequence. Together with result from Theorem 2 and Theorem 2.3 in Bosq (2000), one obtains the following weak convergence of stochastic processes

$$n^{1/2} \widehat{G}(\cdot, \cdot)^{-1/2} (\widehat{m}(\cdot) - m(\cdot)) \rightarrow \zeta(\cdot).$$

Applying Continuous Mapping Theorem for Banach space valued random variables (equation (2.11), Bosq (2000)) to  $\mathcal{C}[0, 1]$ -valued random variables  $n^{1/2} \widehat{G}(\cdot, \cdot)^{-1/2} (\widehat{m}(\cdot) - m(\cdot))$  and  $\zeta(\cdot)$ , one obtains the following weak convergence

$$\begin{aligned}
& \sup_{x \in [0,1]} n^{1/2} \left| \widehat{G}(x, x)^{-1/2} (\widehat{m}(x) - m(x)) \right| \rightarrow \sup_{x \in [0,1]} |\zeta(x)|. \\
& n^{1/2} \left| \widehat{G}(x, x)^{-1/2} (\widehat{m}(x) - m(x)) \right| \rightarrow |\zeta(x)|, x \in [0, 1].
\end{aligned}$$

The Corollary is thus proved.

## S.6 Proof of Theorem 3

According to Theorems 1 and 2, one has

$$\sup_{x \in [0,1]} \left| n_1^{1/2} G_1(x, x)^{-1/2} (\widehat{m}_1(x) - m_1(x)) - \varsigma_1(x) \right| = o_p(1)$$

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and

$$\sup_{x \in [0,1]} \left| n_2^{1/2} G_2(x, x)^{-1/2} (\widehat{m}_2(x) - m_2(x)) - \varsigma_2(x) \right| = o_p(1),$$

where  $\varsigma_i(x)$ ,  $i = 1, 2$  are defined similar way as  $\varsigma(x)$  in the proof of Theorem 2, modified for each group accordingly. Thus  $\varsigma_i(x)$  are standardized Gaussian processes with covariance function

$$\mathbb{E}_{\varsigma_i}(x) \varsigma_i(x') = G_i(x, x') \{G_i(x, x) G_i(x', x')\}^{-1/2}, x, x' \in [0, 1].$$

By the boundness of  $G_i(x, x')$  and  $\lim_{n_1 \rightarrow \infty} \widehat{r} = r > 0$ , one obtains

$$\sup_{x \in [0,1]} \left| \frac{n_1^{1/2} (\widehat{m}_1 - \widehat{m}_2 - m_1 + m_2)(x)}{\{(G_1 + rG_2)(x, x)\}^{1/2}} - \frac{(G_1^{1/2} \varsigma_1 - rG_2^{1/2} \varsigma_2)(x, x)}{\{(G_1 + rG_2)(x, x)\}^{1/2}} \right| = o_p(1).$$

Define  $\varsigma_{12}(x) = (G_1^{1/2} \varsigma_1 - rG_2^{1/2} \varsigma_2)(x, x) \{(G_1 + rG_2)(x, x)\}^{-1/2}$ . Thus

$$\sup_{x \in [0,1]} \left| \frac{n_1^{1/2} (\widehat{m}_1 - \widehat{m}_2 - m_1 + m_2)(x)}{\{(G_1 + rG_2)(x, x)\}^{1/2}} - \varsigma_{12} \right| = o_p(1).$$

It can be calculated that  $\mathbb{E}_{\varsigma_{12}}(x) = 0$  and

$$\mathbb{E}_{\varsigma_{12}}(x) \varsigma_{12}(x') = \frac{(G_1 + rG_2)(x, x')}{\{(G_1 + rG_2)(x, x)\}^{1/2} \{(G_1 + rG_2)(x', x')\}^{1/2}},$$

hence  $\varsigma_{12}(x)$  has the same distribution as  $\zeta_{12}(x)$  since both are standardized Gaussian processes with the same covariance function. The Theorem is thus proved by applying Slutsky's Theorem.