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## SUPPLEMENTARY MATERIAL FOR: A PARTIALLY LINEAR FRAMEWORK FOR MASSIVE HETEROGENOUS DATA

By Tianqi Zhao<sup>‡</sup>, Guang Cheng<sup>§</sup> and Han Liu<sup>‡</sup>

In this supplemental material, we provide the detailed proofs of results presented in the main text. Appendix A contains theoretical justification of RKHS extension to the partially linear function space, as defined in Section 2. Appendix B, C and D present proofs of results in Section 3, 4 and 5 respectively. Appendix E contains proof of lemmas used in proving main theorems. Appendix F proves an exponential inequality for empirical processes in a Banach space, and Appendix G provides proofs of auxiliary lemmas which are used in Appendix E.

## APPENDIX A: RKHS EXTENSION TO PARTIALLY LINEAR FUNCTION SPACE

In this section, we provide detailed theoretical justifications for the RKHS extension to the partially linear space. We first study the properties of the inner product  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$  and its induced kernel  $\widetilde{K}$ , and then prove Proposition 2.3. In the end we provide technical lemmas for the properties of  $R_u$  and  $P_\lambda$ .

A.1. A Collection of Lemmas. The following lemmas are direct consequences of defining the new inner product  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$ . Lemma A.1 proves the existence of kernel  $\tilde{K}$  under the new inner product  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$ , and derives its closed form. Lemma A.2 justifies the existence of the linear operator  $W_{\lambda}$ and derives its closed form. Lemma A.3 studies the asymptotic limit of the  $\boldsymbol{B} - \boldsymbol{A}$ , where recall  $\boldsymbol{A}$  is the Reisz representer of  $\boldsymbol{B} = \mathbb{E}[\boldsymbol{X} \mid Z]$  under the inner product  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$ .

**Lemma A.1.** The linear evaluation functional  $E_z$  of  $\mathcal{H}$  under the inner product  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$  is bounded. Hence  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$  induces a new kernel  $\widetilde{K}(z, z)$  with the form

(A.1) 
$$\widetilde{K}_{z}(\cdot) = \sum_{\ell=1}^{\infty} \frac{\phi_{\ell}(z)}{1 + \lambda/\mu_{\ell}} \phi_{\ell}(\cdot).$$

Moreover, we have that  $\|\widetilde{K}_z\|_{\mathcal{C}} \leq c_{\phi}h^{-1/2}$ , where  $c_{\phi}$  is the constant specified in Assumption 3.2. This implies that  $\|f\|_{\sup} \leq c_{\phi}h^{-1/2}\|f\|_{\mathcal{C}}$  for all  $f \in \mathcal{H}$ .

PROOF. (i) Boundedness of  $E_z$ : We have for any  $f \in \mathcal{H}$ ,

$$|E_z f| = |f(z)| = |\langle f, K_z \rangle_{\mathcal{H}}| \le ||K_z||_{\mathcal{H}} ||f||_{\mathcal{H}} \le \lambda^{-1/2} c_k ||f||_{\mathcal{C}},$$

where the last inequality follows from the relationship  $\lambda ||f||_{\mathcal{H}}^2 \leq ||f||_{\mathcal{C}}$  implied by the definition of  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$ . It follows that  $E_z$  is bounded.

(ii) Existence and exact form of K: By Definition 2.1, we have that  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$  induces a new kernel  $\widetilde{K}(z, z)$ . As  $\widetilde{K}_z \in \mathcal{H}$  for all  $z \in \mathcal{Z}$ , by Fourier expansion,  $\widetilde{K}_z = \sum_{\ell=1}^{\infty} \kappa_\ell \phi_\ell$ . Then we have

$$\kappa_{\ell} = \langle \widetilde{K}_z, \phi_{\ell} \rangle_{L_2(\mathbb{P}_Z)} = \langle \widetilde{K}_z, \phi_{\ell} \rangle_{\mathcal{C}} - \lambda \langle \widetilde{K}_z, \phi_{\ell} \rangle_{\mathcal{H}} = \phi_{\ell}(z) - \lambda \kappa_{\ell} / \mu_{\ell}.$$

Solving for  $\kappa_{\ell}$ , we have  $\kappa_{\ell} = \phi_{\ell}(z)/(1 + \lambda/\mu_{\ell})$ . Hence we get the formula for  $\widetilde{K}_z(\cdot)$  in (A.1).

(iii) Uniform bound of  $\widetilde{K}_z$ : By (A.1) and reproducing property, we have that

$$\|\widetilde{K}_z\|_{\mathcal{C}}^2 = \langle \widetilde{K}_z, \widetilde{K}_z \rangle_{\mathcal{C}} = \widetilde{K}(z, z)$$
$$= \sum_{\ell=1}^{\infty} \frac{\phi_\ell^2(z)}{1 + \lambda/\mu_\ell} \le c_\phi^2 h^{-1}.$$

as desired. Hence for all  $z \in \mathcal{Z}$ ,

$$|f(z)| \le ||f||_{\mathcal{C}} ||\widetilde{K}_z||_{\mathcal{C}} \le c_{\phi} h^{-1/2} ||f||_{\mathcal{C}},$$

by Cauchy-Schwarz. This implies that  $||f||_{\sup} \leq c_{\phi} h^{-1/2} ||f||_{\mathcal{C}}$  for all  $f \in \mathcal{H}$ .

**Lemma A.2.** There exists a bounded linear operator  $W_{\lambda} : \mathcal{H} \to \mathcal{H}$  such that for any  $f, \tilde{f} \in \mathcal{H}$ , we have

(A.2) 
$$\langle W_{\lambda}f, \tilde{f}\rangle_{\mathcal{C}} = \lambda \langle f, \tilde{f}\rangle_{\mathcal{H}}$$

Moreover, we have for all eigenfunctions  $\phi_{\ell}$ ,  $\ell = 1, 2, ...$ 

(A.3) 
$$W_{\lambda}\phi_{\ell}(\cdot) = \frac{\lambda}{\lambda + \mu_{\ell}}\phi_{\ell}(\cdot).$$

PROOF. The proof for the existence of  $W_{\lambda}$  uses Riesz representation theorem. Define the bilinear form  $V(f, \tilde{f}) := \lambda \langle f, \tilde{f} \rangle_{\mathcal{H}}$ , for any  $f, \tilde{f} \in \mathcal{H}$ . For any fixed f, this defines a functional  $V_f(\cdot) = V(f, \cdot)$ . It is easy to verify that  $V_f$  is linear. Moreover,  $V_f$  is bounded under the inner product  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$ , as

$$|V_f(\widetilde{f})| = |\lambda \langle f, \widetilde{f} \rangle_{\mathcal{H}}| \le \lambda ||f||_{\mathcal{H}} ||\widetilde{f}||_{\mathcal{H}} \le \lambda^{1/2} ||f||_{\mathcal{H}} ||\widetilde{f}||_{\mathcal{C}},$$

for all  $\tilde{f} \in \mathcal{H}$ . Hence by Riesz representation theorem, there exists an unique element  $f_1 \in \mathcal{H}$  such that  $V_f(\tilde{f}) = \langle f_1, \tilde{f} \rangle_{\mathcal{C}}$  for all  $\tilde{f} \in \mathcal{H}$ . We let  $W_{\lambda}f = f_1$ ,

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and it follows that  $\langle W_{\lambda}f, \tilde{f} \rangle_{\mathcal{C}} = \lambda \langle f, \tilde{f} \rangle_{\mathcal{H}}$  for all  $f, \tilde{f} \in \mathcal{H}$ . We next prove linearity of  $W_{\lambda}$ . By definition, for any  $f_1, f_2, \tilde{f} \in \mathcal{H}$  and  $a, b \in \mathbb{R}$ , we have

$$\langle W_{\lambda}(af_1 + bf_2), \tilde{f} \rangle_{\mathcal{C}} = \lambda \langle af_1 + bf_2, \tilde{f} \rangle_{\mathcal{H}} = a\lambda \langle f_1, \tilde{f} \rangle_{\mathcal{H}} + b\lambda \langle f_2, \tilde{f} \rangle_{\mathcal{H}} = \langle aW_{\lambda}f_1 + bW_{\lambda}f_2, \tilde{f} \rangle_{\mathcal{C}},$$

which implies  $W_{\lambda}(af_1 + bf_2) = aW_{\lambda}f_1 + bW_{\lambda}f_2$ .

Furthermore,  $W_{\lambda}$  is a bounded operator under  $\|\cdot\|_{\mathcal{C}}$ , as for any  $f \in \mathcal{H}$ 

$$\begin{split} \|W_{\lambda}f\|_{\mathcal{C}} &= \sup_{\|\widetilde{f}\|_{\mathcal{C}} \leq 1} \langle W_{\lambda}f, f \rangle_{\mathcal{C}} \\ &= \sup_{\|\widetilde{f}\|_{\mathcal{C}} \leq 1} \lambda \langle \lambda f, \widetilde{f} \rangle_{\mathcal{H}} \\ &\leq \lambda \|f\|_{\mathcal{H}} \sup_{\|\widetilde{f}\|_{\mathcal{C}} \leq 1} \|\widetilde{f}\|_{\mathcal{H}} \\ &\leq \|f\|_{\mathcal{C}}, \end{split}$$

where the last inequality follows from the fact that  $\lambda^{1/2} \|f\|_{\mathcal{H}} \leq \|f\|_{\mathcal{C}}$  implied by the definition of  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$ . This shows that  $W_{\lambda}$  has operator norm bounded by 1.

To prove the second half of the lemma, we have that  $\langle W_{\lambda}f, \tilde{f} \rangle_{\mathcal{C}} = \lambda \langle f, \tilde{f} \rangle_{\mathcal{H}}$ . Also, by the definition of  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$  we have  $\langle W_{\lambda}f, \tilde{f} \rangle_{\mathcal{C}} = \langle W_{\lambda}f, \tilde{f} \rangle_{L_2(P_Z)} +$  $\lambda \langle W_{\lambda} f, \widetilde{f} \rangle_{\mathcal{H}}$ . It follows from the two equations that

(A.4) 
$$\langle W_{\lambda}f, \tilde{f} \rangle_{L_2(\mathbb{P}_Z)} = \lambda \langle (id - W_{\lambda})f, \tilde{f} \rangle_{\mathcal{H}},$$

for any  $f, \tilde{f} \in \mathcal{H}$ .  $W_{\lambda}\phi_{\ell}$  has a Fourier expansion:  $W_{\lambda}\phi_{\ell} = \sum_{k=1}^{\infty} w_k\phi_k$ . Letting  $f = \tilde{f} = \phi_{\ell}$  in (A.4) yields  $w_{\ell} = \lambda/(\lambda + \mu_{\ell})$ , and letting  $f = \phi_{\ell}$  and  $\tilde{f} = \phi_{r}$ in (A.4) yields  $w_r = 0$  for  $r \neq \ell$ . Hence the conclusion follows. 

**Lemma A.3.** We have the following equations hold:

(A.5) 
$$\lim_{\lambda \to 0} \mathbb{E} \Big[ \boldsymbol{X} \big( \boldsymbol{B}(Z) - \boldsymbol{A}(Z) \big)^T \Big] = 0$$

(A.6) 
$$\lim_{\lambda \to 0} \mathbb{E} \Big[ \boldsymbol{B}(Z) \big( \boldsymbol{B}(Z) - \boldsymbol{A}(Z) \big)^T \Big] = 0$$

(A.7) 
$$\lim_{\lambda \to 0} \mathbb{E} \left[ \left( \boldsymbol{B}(Z) - \boldsymbol{A}(Z) (\boldsymbol{B}(Z) - \boldsymbol{A}(Z))^T \right) \right] = 0$$

The lemma shows that the difference B - A goes to zero as  $\lambda \to 0$ . Intuititively, as  $\lambda \to 0$ , the inner product  $\langle \cdot, \cdot \rangle_{\mathcal{C}}$  converges to  $\langle \cdot, \cdot \rangle_{L_2(\mathbb{P}_Z)}$  by its definition, hence the the representer A of B converges to B itself. The following is the formal proof of this lemma.

PROOF. By reproducing property of  $\widetilde{K}_z$ , the definition of  $A_k$  and (A.1), we have

(A.8) 
$$A_k(z) = \langle A_k, \widetilde{K}_z \rangle_{\mathcal{C}} = \langle B_k, \widetilde{K}_z \rangle_{L_2(\mathbb{P}_Z)} = \sum_{i=1}^{\infty} \frac{\langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)}}{1 + \lambda/\mu_i} \phi_i(z).$$

By Fourier expansion of  $B_k$ , it follows from the above equation that

(A.9) 
$$B_k(z) - A_k(z) = \sum_{i=1}^{\infty} \frac{\langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)} \lambda/\mu_i}{1 + \lambda/\mu_i} \phi_i(z) \to 0,$$

As  $\phi_i$  are uniformly bounded and  $\sum_{i=1}^{\infty} \langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)} \leq \infty$ , it follows from dominated convergence theorem that  $B_k(z) - A_k(z) \to 0$  for all  $z \in \mathbb{Z}$ . Therefore (A.7) holds. Moreover,

$$\mathbb{E}[B_j(Z)(B_k(Z) - A_k(Z))] = \langle B_k, B_k - A_k \rangle_{L_2(\mathbb{P}_Z)}$$
(A.10)  

$$= \sum_{i=1}^{\infty} \frac{\lambda/\mu_i}{1 + \lambda/\mu_i} \langle B_j, \phi_i \rangle_{L_2(\mathbb{P}_Z)} \langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)}$$

$$\to 0,$$

where the second equality is by (A.9) and the limit is by dominated convergence theorem. Hence (A.6) holds. Lastly,

$$\mathbb{E}\big[X_j(B_k(Z) - A_k(Z))\big] = \sum_{i=1}^{\infty} \frac{\lambda/\mu_i}{1 + \lambda/\mu_i} \langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)} \mathbb{E}[X_j \phi_i(Z)] \to 0,$$

again by dominated convergence and the fact that  $X_j$  and  $\phi_i$  are uniformly bounded. Hence (A.5) also holds.

**A.2.** Proof of Proposition 2.3. With the theoretical foundations laid up in the previous section, we are now ready to construct  $R_u$  and  $P_{\lambda}$ , whose exact forms are presented in Proposition 2.3.

PROOF. The proof follows similarly as Proposition 2.1 in Cheng and Shang (2013). We first want to construct  $R_u \in \mathcal{A}$  such that it possess the following reproducing property:

(A.11) 
$$\langle R_u, m \rangle_{\mathcal{A}} = \boldsymbol{\beta}^T \boldsymbol{x} + f(z),$$

for any  $u = (\boldsymbol{x}, z)$  and  $m = (\boldsymbol{\beta}, f) \in \mathcal{A}$ . As  $R_u \in \mathcal{A}$ , it has two components:

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$$R_{u} = (L_{u}, N_{u}). \text{ Hence the L.H.S. of (A.11) can be written as}$$

$$\langle R_{u}, m \rangle_{\mathcal{A}} = \mathbb{E} \left[ (\mathbf{X}^{T} L_{u} + N_{u}(Z)) (\mathbf{X}^{T} \boldsymbol{\beta} + f(Z)) \right] + \lambda \langle N_{u}, f \rangle_{\mathcal{H}}$$

$$= \boldsymbol{\beta}^{T} \mathbb{E} [\mathbf{X} \mathbf{X}^{T}] L_{u} + \boldsymbol{\beta}^{T} \mathbb{E} [\mathbf{X} N_{u}(Z)] + L_{u}^{T} \mathbb{E} [\mathbf{X} f(Z)]$$

$$+ \mathbb{E} [N_{u}(Z) f(Z)] + \lambda \langle N_{u}, f \rangle_{\mathcal{H}}$$

$$= \boldsymbol{\beta}^{T} \left( \mathbb{E} [\mathbf{X} \mathbf{X}^{T}] L_{u} + \mathbb{E} [\mathbf{B}(Z) N_{u}(Z)] \right) + L_{u}^{T} \mathbb{E} [\mathbf{B}(Z) f(Z)] + \langle N_{u}, f \rangle_{\mathcal{C}}$$
(A.12)

$$= \boldsymbol{\beta}^{T} \left( \mathbb{E}[\boldsymbol{X}\boldsymbol{X}^{T}]L_{u} + \mathbb{E}[\boldsymbol{B}(Z)N_{u}(Z)] \right) + \langle \boldsymbol{A}^{T}L_{u} + N_{u}, f \rangle_{\mathcal{C}}$$

where in the second last inequality we used the definition of  $\langle\cdot,\cdot\rangle_{\mathcal{C}}$  and in the last equality we used  $\mathbb{E}[\boldsymbol{B}(Z)f(Z)] = \langle \boldsymbol{B}, f \rangle_{L_2(\mathbb{P}_Z)} = \langle \boldsymbol{A}, f \rangle_{\mathcal{C}}$ . On the other hand, the R.H.S of (A.11) is

(A.13) 
$$\boldsymbol{\beta}^T \boldsymbol{x} + f(z) = \boldsymbol{\beta}^T \boldsymbol{x} + \langle \widetilde{K}_z, f \rangle.$$

Comparing (A.12) and (A.13), we have the following set of equations:

$$\boldsymbol{x} = \mathbb{E}[\boldsymbol{X}\boldsymbol{X}^T]L_u + \mathbb{E}[\boldsymbol{B}(Z)N_u(Z)]$$
$$\widetilde{K}_z = \boldsymbol{A}^T L_u + N_u.$$

From the second equation we get  $N_u = \widetilde{K}_z - \mathbf{A}^T L_u$ . Substitute it into the first equation, we get

$$\begin{aligned} \boldsymbol{x} &= \mathbb{E}[\boldsymbol{X}\boldsymbol{X}^{T}]L_{u} + \mathbb{E}[\boldsymbol{B}(Z)(\widetilde{K}_{z}(Z) - \boldsymbol{A}(Z)^{T}L_{u})] \\ &= \left(\Omega + \mathbb{E}[\boldsymbol{B}(Z)\boldsymbol{B}^{T}(Z)]\right)L_{u} + \mathbb{E}[\boldsymbol{B}(Z)\widetilde{K}_{z}(Z)] - \mathbb{E}[\boldsymbol{B}(Z)\boldsymbol{A}(Z)^{T}L_{u}] \\ &= (\Omega + \Sigma_{\lambda})L_{u} + \langle \boldsymbol{B}, \widetilde{K}_{z} \rangle_{L_{2}(\mathbb{P}_{Z})} \\ &= (\Omega + \Sigma_{\lambda})L_{u} + \langle \boldsymbol{A}, \widetilde{K}_{z} \rangle_{\mathcal{C}} = (\Omega + \Sigma_{\lambda})L_{u} + \boldsymbol{A}(z), \end{aligned}$$

where in the second inequality we used the fact that B(Z) and X - B(Z)are orthogonal. Therefore it follows that

$$L_u = (\Omega + \Sigma_\lambda)^{-1} (\boldsymbol{x} - \boldsymbol{A}(z)).$$

This finishes the proof for the construction of  $R_u$ .

We next construct  $P_{\lambda}$  such that

(A.14) 
$$\langle P_{\lambda}m, \widetilde{m} \rangle_{\mathcal{A}} = \lambda \langle f, \widetilde{f} \rangle_{\mathcal{H}},$$

for any  $m = (\beta, f), \widetilde{m} = (\widetilde{\beta}, \widetilde{f}) \in \mathcal{A}$ . As  $P_{\lambda}m \in \mathcal{A}$ , it has two components:  $P_{\lambda}m = (L_{\lambda}f, N_{\lambda}f)$ . Similar to the derivation of (A.12), the L.H.S. of (A.14) can be written as

$$\langle P_{\lambda}m, \widetilde{m} \rangle_{\mathcal{A}} = \mathbb{E} \left[ (\mathbf{X}^{T} L_{\lambda} f + N_{\lambda} f(Z)) (\mathbf{X}^{T} \widetilde{\boldsymbol{\beta}} + \widetilde{f}) \right] + \lambda \langle N_{\lambda} f, \widetilde{f} \rangle_{\mathcal{H}}$$

$$(A.15) \qquad = \widetilde{\boldsymbol{\beta}}^{T} \left( \mathbb{E} [\mathbf{X} \mathbf{X}^{T}] L_{\lambda} f + \mathbb{E} [\mathbf{B}(Z) N_{\lambda} f(Z)] \right) + \langle \mathbf{A}^{T} L_{\lambda} f + N_{\lambda} f, \widetilde{f} \rangle_{\mathcal{C}}$$

The R.H.S. of (A.14) is

(A.16) 
$$\lambda \langle f, f \rangle_{\mathcal{H}} = \langle W_{\lambda} f, f \rangle_{\mathcal{C}}$$

Comparing (A.15) and (A.16), we obtain the following set of equations:

$$\mathbf{0} = \mathbb{E}[\boldsymbol{X}\boldsymbol{X}^T]L_{\lambda}f + \mathbb{E}[\boldsymbol{B}(Z)N_{\lambda}f(Z)]$$
$$W_{\lambda}f = \boldsymbol{A}^T L_{\lambda}f + N_{\lambda}f.$$

Solving the above two equations, we get

$$L_{\lambda}f = -(\Omega + \Sigma_{\lambda})^{-1} \langle \boldsymbol{B}, W_{\lambda}f \rangle_{L_{2}(\mathbb{P}_{Z})} \text{ and } N_{\lambda}f = W_{\lambda}f - \boldsymbol{A}^{T}L_{\lambda}f,$$
  
as desired.

A.3. Properties of  $R_u$  and  $P_{\lambda}$ . We first present a lemma that bounds the  $\mathcal{A}$ -norm of  $R_u$ .

**Lemma A.4.** There exists a constant  $c_r > 0$  independent to u such that  $||R_u||_{\mathcal{A}} \leq c_r h^{-1/2}$ . It follows that  $||m||_{\sup} \leq c_r h^{-1/2} ||m||_{\mathcal{A}}$  for all m.

PROOF. By Proposition 2.3, we have that for u = (x, z),

(A.17)  

$$\langle R_u, R_u \rangle_{\mathcal{A}} = \boldsymbol{x}^T L_u + N_u(z)$$

$$= \widetilde{K}_z(z) + (\boldsymbol{x} - \boldsymbol{A}(z))^T L_u$$

$$= \widetilde{K}_z(z) + (\boldsymbol{x} - \boldsymbol{A}(z))^T (\Omega + \Sigma_\lambda)^{-1} (\boldsymbol{x} - \boldsymbol{A}(z)).$$

From Lemma A.1, we have  $\widetilde{K}_z(z) = \|\widetilde{K}\|_{\mathcal{C}}^2 \leq c_{\phi}^2 h^{-1}$ . For the second term in (A.17), we first show that  $\Sigma_{\lambda}$  is positive definite. Recall the definition of  $\Sigma_{\lambda} = \mathbb{E}[\mathbf{B}(Z)(\mathbf{B}(Z) - \mathbf{A}(Z))]$ . (A.10) shows that

$$[\Sigma_{\lambda}]_{jk} = \mathbb{E} \Big[ B_j(Z) (B_k(Z) - A_k(Z)) \Big] = \sum_{\ell=1}^{\infty} \frac{\lambda/\mu_\ell}{1 + \lambda/\mu_\ell} \langle B_j, \phi_\ell \rangle_{L_2} \langle B_k, \phi_\ell \rangle_{L_2},$$

which implies that  $\Sigma_{\lambda}$  is positive definite. Indeed, for any  $\boldsymbol{x} \in \mathbb{R}^p$  and  $\boldsymbol{x} \neq 0$ ,

$$\boldsymbol{x}^T \Sigma_{\lambda} \boldsymbol{x} = \sum_{j=1}^p \sum_{k=1}^p x_j x_k [\Sigma_{\lambda}]_{jk} = \sum_{\ell=1}^\infty \frac{\lambda/\mu_\ell}{1+\lambda/\mu_\ell} \Big(\sum_{j=1}^p x_j \langle B_j, \phi_\ell \rangle_{L_2}\Big)^2 > 0.$$

Therefore, it follows that the second term in (A.17) is bounded by

$$(\boldsymbol{x} - \boldsymbol{A}(z))^{T} (\Omega + \Sigma_{\lambda})^{-1} (\boldsymbol{x} - \boldsymbol{A}(z)) \leq \|\Omega + \Sigma_{\lambda}\|^{-1} \|\boldsymbol{x} - \boldsymbol{A}(z)\|_{2}^{2}$$
  
(A.18) 
$$\leq \tau_{\min}(\Omega)^{-1} \|\boldsymbol{x} - \boldsymbol{A}(z)\|_{2}^{2}.$$

where recall  $\tau_{\min}(\Omega)$  is the minimum eigenvalue of  $\Omega$ . As  $\boldsymbol{x}$  is uniformly

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bounded, we are left to bound A(z). By (A.8), we have

(A.19) 
$$A_k(z) = \sum_{\ell=1}^{\infty} \frac{\langle B_k, \phi_\ell \rangle_{L_2(\mathbb{P}_Z)}}{1 + \lambda/\mu_\ell} \phi_\ell(z),$$

Hence by the assumption that  $B_j \in L_2(\mathbb{P}_Z)$  for  $j = 1, \ldots, p$  and uniform boundedness of  $\phi_{\ell}$ , we have

(A.20) 
$$A_k^2(z) \le c_{\phi} \sum_{\ell=1}^{\infty} \langle B_k, \phi_\ell \rangle_{L_2(\mathbb{P}_Z)}^2 \sum_{\ell=1}^{\infty} (1 + \lambda/\mu_\ell)^{-2} \le c_{\phi} \|B_k\|_{L_2(\mathbb{P}_Z)}^2 h^{-1}.$$

Therefore, by (A.17) and (A.18), we have  $||R_u||_{\mathcal{A}} \leq c_r h^{-1/2}$ , where  $c_r$  is determined by  $p, c_{\phi}, c_x, \tau_{\min}$  and  $||B_k||_{L_2(\mathbb{P}_Z)}$ . Therefore, for any u = (x, z)

$$|m(u)| = |\langle m, R_u \rangle_{\mathcal{A}}| \le ||m||_{\mathcal{A}} ||R_u||_{\mathcal{A}} \le c_r h^{-1/2} ||m||_{\mathcal{A}},$$

which implies that  $||m||_{\sup} \leq c_r h^{-1/2} ||m||_{\mathcal{A}}$ .

Based on the above lemma, if we have the extra condition that  $B_k(z)$  are smooth functions, then we can bound the parametric and nonparametric components of  $R_u$  and  $P_{\lambda}m_0$  more precisely.

Lemma A.5. Suppose Assumptions 3.1 - 3.3 hold. Then we have

- (i)  $||L_u||_2^2 \leq C'_1$  where  $C'_1 = 2\tau_{\min}^{-2} \left( c_x^2 p + c_\phi^2 \operatorname{Tr}(K) \sum_{k=1}^p ||B_k||_{\mathcal{H}}^2 \right)$ , and
- $||N_u||_{\mathcal{C}}^2 \leq C_1 h^{-1} \text{ where } C_1 = 2c_{\phi}^2 \left( 1 + C_1' \sum_{k=1}^p ||B_k||_{L_2(\mathbb{P}_Z)}^2 \right);$ (ii) Moreover,  $||L_{\lambda} f_0||_2^2 \leq C_2' \lambda^2$  and  $||N_{\lambda} f_0||_{\mathcal{C}}^2 \leq 2||f_0||_{\mathcal{H}}^2 \lambda + C_2 \lambda^2$ , where  $C_2' = \tau_{\min}^{-2} ||f_0||_{\mathcal{H}}^2 \sum_{k=1}^p ||B_k||_{\mathcal{H}}^2$  and  $C_2 = 2C_2' \sum_{k=1}^p ||B_k||_{L_2(\mathbb{P}_Z)}^2.$

PROOF. (i) By Proposition 2.3,

$$L_u = (\Omega + \Sigma_\lambda)^{-1} (\boldsymbol{x} - \boldsymbol{A}(z)) \text{ and } N_u = \widetilde{K}_z - \boldsymbol{A}^T L_u,$$

By the first equation we have

$$||L_u||_2^2 \le ||(\Omega + \Sigma_\lambda)^{-1}||_2^2 ||\boldsymbol{x} - \boldsymbol{A}(z)||_2^2.$$

Recall

$$A_k(z) = \sum_{\ell=1}^{\infty} \frac{\langle B_k, \phi_\ell \rangle_{L_2}}{1 + \lambda/\mu_\ell} \phi_\ell(z).$$

Hence by Assumption 3.3 it follows that

$$A_k(z)^2 \le \sum_{\ell=1}^{\infty} \frac{\langle B_k, \phi_\ell \rangle_{L_2}^2}{\mu_\ell} \sum_{\ell=1}^{\infty} \mu_\ell \frac{\phi_\ell(z)^2}{(1+\lambda/\mu_\ell)^2} \le c_\phi^2 \|B_k\|_{\mathcal{H}}^2 \operatorname{Tr}(K),$$

where the first inequality is by Cauchy-Schwarz and the second is by As-

sumption 3.2 that  $\phi_{\ell}$  are uniformly bounded. Hence for all  $z \in \mathcal{Z}$ ,

(A.21) 
$$\|\boldsymbol{A}(z)\|_{2}^{2} \leq c_{\phi}^{2} \operatorname{Tr}(K) \sum_{k=1}^{p} \|B_{k}\|_{\mathcal{H}}^{2}.$$

Also, we showed in the proof of Lemma A.4 that  $\|(\Omega + \Sigma_{\lambda})^{-1}\|$  is bounded by  $\tau_{\min}^{-1}$ . Finally, by the boundedness of the support of  $\mathcal{X}$ , we have

$$||L_U||_2^2 \le 2\tau_{\min}^{-2} \left( c_x^2 p + c_\phi^2 \operatorname{Tr}(K) \sum_{k=1}^p ||B_k||_{\mathcal{H}}^2 \right) = C_1'.$$

To control  $N_u$ , we have

(A.22) 
$$\|N_u\|_{\mathcal{C}}^2 \le 2\left(\|\widetilde{K}_z\|_{\mathcal{C}}^2 + \|L_u^T \boldsymbol{A}\|_{\mathcal{C}}^2\right)$$

For the first term in (A.22), by Lemma A.1, we have  $\|\widetilde{K}_z\|_{\mathcal{C}}^2 \leq c_{\phi}^2 h^{-1}$ . For the second term, by (A.19) we have

(A.23) 
$$\|A_k\|_{\mathcal{C}}^2 = \langle A_k, A_k \rangle_{\mathcal{C}} = \langle B_k, A_k \rangle_{L_2(\mathbb{P}_Z)} = \sum_{\ell=1}^{\infty} \frac{\langle B_k, \phi_\ell \rangle_{L_2(\mathbb{P}_Z)}^2}{1 + \lambda/\mu_\ell}$$
$$\leq c_{\phi}^2 \|B_k\|_{L_2(\mathbb{P}_Z)}^2 \sum_{\ell=1}^{\infty} \frac{1}{1 + \lambda/\mu_\ell} = c_{\phi}^2 \|B_k\|_{L_2(\mathbb{P}_Z)}^2 h^{-1}.$$

where the inequality is by Cauchy-Schwartz and uniform boundedness of  $\phi_\ell.$  Hence it follows that

$$\|L_{u}^{T}\boldsymbol{A}\|_{\mathcal{C}} = \|\sum_{k=1}^{p} (L_{u})_{k}A_{k}\|_{\mathcal{C}} \leq \sum_{k=1}^{p} |(L_{u})_{k}|\|A_{k}\|_{\mathcal{C}}$$
(A.24) 
$$\leq \|L_{u}\|_{2} \Big(\sum_{k=1}^{p} \|A_{k}\|_{\mathcal{C}}^{2}\Big)^{1/2} \leq (C_{1}')^{1/2} c_{\phi} h^{-1/2} \Big(\sum_{k=1}^{p} \|B_{k}\|_{L_{2}(\mathbb{P}_{Z})}^{2}\Big)^{1/2}$$

Therefore, by (A.22) we obtain

$$\|N_u\|_{\mathcal{C}}^2 \le 2c_{\phi}^2 \Big(1 + C_1' \sum_{k=1}^p \|B_k\|_{L_2(\mathbb{P}_Z)}^2 \Big) h^{-1} = C_1 h^{-1}$$

(ii) By Proposition 2.3, we have

$$L_{\lambda}f_{0} = -(\Omega + \Sigma_{\lambda})^{-1} \langle W_{\lambda}f_{0}, \boldsymbol{B} \rangle_{L_{2}(\mathbb{P}_{Z})}$$
$$N_{\lambda}f_{0} = (L_{\lambda}f_{0})^{T}\boldsymbol{A} + W_{\lambda}f_{0}$$

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To control  $L_{\lambda} f_0$ , we have by Fourier expansion of  $f_0$  and (A.3)

$$\langle B_j, W_{\lambda} f_0 \rangle_{L_2(\mathbb{P}_Z)}^2 = \left( \sum_{\ell=1}^{\infty} \langle B_k, \phi_\ell \rangle_{L_2} \frac{\lambda \theta_\ell}{\mu_\ell + \lambda} \right)^2$$

$$\leq \lambda^2 \left( \sum_{i=1}^{\infty} \frac{\langle B_k, \phi_\ell \rangle_{L_2}^2}{\mu_\ell + \lambda} \right) \left( \sum_{\ell=1}^{\infty} \frac{\theta_\ell^2}{\mu_\ell + \lambda} \right)$$

$$\leq \lambda^2 \|B_k\|_{\mathcal{H}}^2 \|f_0\|_{\mathcal{H}}^2.$$

Hence by the positive definiteness of  $\Sigma_{\lambda}$ , we have

$$|L_{f_0}||_2^2 \le \|(\Omega + \Sigma_{\lambda})^{-1}\| \| \langle W_{\lambda} f_0, \boldsymbol{B} \rangle_{L_2(\mathbb{P}_Z)} \|_2^2$$
  
$$\le \tau_{\min}^{-2} \| f_0 \|_{\mathcal{H}}^2 \sum_{k=1}^p \| B_k \|_{\mathcal{H}}^2 \lambda^2 = C_2' \lambda^2.$$

For  $N_{\lambda}f_0$ , we have

(A.25)  $\|N_{\lambda}f_{0}\|_{\mathcal{C}}^{2} = 2\|(L_{\lambda}f_{0})^{T}\boldsymbol{A}\|_{\mathcal{C}}^{2} + 2\|W_{\lambda}f_{0}\|_{\mathcal{C}}^{2}$ 

For the first term (A.25), by the fact that  $\sum_{\ell=1}^{\infty} \langle B_k, \phi_\ell \rangle_{L_2(\mathbb{P}_Z)}^2 = \|B_k\|_{L_2(\mathbb{P}_Z)}^2$ , we first get an inequality for  $\|A_k\|_{\mathcal{C}}^2$  that is different than (A.23):

$$\|A_k\|_{\mathcal{C}}^2 = \langle A_k, A_k \rangle_{\mathcal{C}} = \langle B_k, A_k \rangle_{L_2(\mathbb{P}_Z)} = \sum_{\ell=1}^{\infty} \frac{\langle B_k, \phi_\ell \rangle_{L_2(\mathbb{P}_Z)}^2}{1 + \lambda/\mu_\ell} \le \|B_k\|_{L_2(\mathbb{P}_Z)}^2.$$

Therefore, following the same derivation as (A.24), we have

$$\|(L_{\lambda}f_{0})^{T}\boldsymbol{A}\|_{\mathcal{C}}^{2} \leq \|L_{\lambda}f_{0}\|_{2}^{2} \sum_{k=1}^{p} \|A_{k}\|_{\mathcal{C}}^{2} \leq C_{2}'\lambda^{2} \sum_{k=1}^{p} \|B_{k}\|_{L_{2}(\mathbb{P}_{Z})}^{2}.$$

For the second term in (A.25) we have

$$\begin{aligned} \|W_{\lambda}f_{0}\|_{\mathcal{C}} &= \sup_{\|f\|_{\mathcal{C}}=1} |\langle W_{\lambda}f_{0}, f\rangle_{\mathcal{C}}| = \sup_{\|f\|_{\mathcal{C}}=1} \lambda |\langle f_{0}, f\rangle_{\mathcal{H}}| \\ &\leq \sup_{\|f\|_{\mathcal{C}}=1} \sqrt{\lambda \|f_{0}\|_{\mathcal{H}}^{2}} \sqrt{\lambda \|f\|_{\mathcal{H}}^{2}} \leq \lambda^{1/2} \|f_{0}\|_{\mathcal{H}}, \end{aligned}$$

where the last equality follows from the fact that  $\lambda \|f\|_{\mathcal{H}}^2 \leq \|f\|_{\mathcal{C}}^2$ . Therefore, by (A.25), we obtain

$$\|N_{\lambda}f_0\|_{\mathcal{C}}^2 \le 2\lambda \|f_0\|_{\mathcal{H}}^2 + 2C_2'\lambda^2 \sum_{k=1}^p \|B_k\|_{L_2(\mathbb{P}_Z)}^2 = 2\|f_0\|_{\mathcal{H}}^2\lambda + C_2\lambda^2,$$

as desired.

#### APPENDIX B: PROOFS IN SECTION 3

## B.1. Proof of Theorem 3.5.

**PROOF.** By first order optimality condition, we have

$$\sum_{i \in L_j} \boldsymbol{X}_i (Y_i - \boldsymbol{X}_i^T \boldsymbol{\check{\beta}}^{(j)} - \bar{f}(Z_i)) = 0.$$

Hence we have

(B.1) 
$$\check{\boldsymbol{\beta}}^{(j)} = \Big(\sum_{i \in L_j} \boldsymbol{X}_i \boldsymbol{X}_i^T\Big)^{-1} \sum_{i \in L_j} \boldsymbol{X}_i \big(Y_i - \bar{f}(Z_i)\big).$$

As for  $i \in L_j$  we have  $Y_i = \mathbf{X}_i^T \boldsymbol{\beta}_0^{(j)} + f_0(Z_i) + \varepsilon_i$ , hence

(B.2) 
$$\sqrt{n}(\check{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_0) = n^{-1/2} \sum_{i \in L_j} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \boldsymbol{X}_i \varepsilon_i + n^{-1/2} \sum_{i \in L_j} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \boldsymbol{X}_i (f_0(Z_i) - \bar{f}(Z_i)),$$

where the  $\widehat{\Sigma}^{(j)} = \frac{1}{n} \sum_{i \in L_j} X_i X_i^T$  is sample covariance of X based on data from the *j*-th subpopulation. For the first term on the R.H.S. of (B.2), it is the same as the one for ordinary least squares, and so

(B.3) 
$$n^{-1/2} \sum_{i \in L_j} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \boldsymbol{X}_i \varepsilon_i \rightsquigarrow N(0, \sigma^2 \Sigma^{-1}).$$

For the second term on the R.H.S. of (B.2), by triangular inequality, we have for all  $1 \le j \le s$  that

$$\begin{aligned} \left\| \frac{1}{\sqrt{n}} \sum_{i \in L_j} \left( \widehat{\boldsymbol{\Sigma}}^{(j)} \right)^{-1} \boldsymbol{X}_i \left( f_0(Z_i) - \bar{f}(Z_i) \right) \right\|_2 &\leq \|\bar{f} - f_0\|_{\sup} n^{-1/2} \sum_{i \in L_j} \| \widehat{\boldsymbol{\Sigma}}^{(j)} \boldsymbol{X}_i \|_2 \\ &\leq C n^{1/2} \| \bar{f} - f_0 \|_{\sup}, \end{aligned}$$

for some constant C that is related to the dimension p and boundedness of the support of  $\mathcal{X}$ . As  $\|\bar{f} - f_0\|_{\sup} \leq \|\bar{m} - m_0\|_{\sup} \leq c_r h^{-1/2} \|\bar{m} - m_0\|_{\mathcal{A}}$  by Lemma A.4, it suffices to bound  $\|\bar{m} - m_0\|_{\mathcal{A}}$ . Taking average of equations (7.2) for all j over s, we get

$$\bar{m} - m_0 = \frac{1}{N} \sum_{i=1}^N R_{U_i} \varepsilon_i - P_\lambda m_0 - \frac{1}{s} \sum_{j=1}^s Rem^{(j)}.$$

By triangular inequality,

(B.4) 
$$\|\bar{m} - m_0\|_{\mathcal{A}} \le \|\frac{1}{N} \sum_{i=1}^N R_{U_i} \varepsilon_i\|_{\mathcal{A}} + \|P_{\lambda}m_0\|_{\mathcal{A}} + \|\frac{1}{s} \sum_{j=1}^s Rem^{(j)}\|_{\mathcal{A}}.$$

For the first term on the R.H.S., define  $Q_i = \{|\varepsilon_i| \leq \log N\}$ . Since  $||R_U||_{\mathcal{A}} \leq c_r h^{-1/2}$ , we have that  $\{\varepsilon_i R_{U_i} I_{Q_i}\}_{i=1}^N$  is a sequence of random variables in

Hilbert space  $\mathcal{F}$  that are i.i.d. with mean zero and bounded by  $c_r h^{-1/2} \log N$ . Therefore by Lemma G.1 we have

$$\mathbb{P}\Big(\|\frac{1}{N}\sum_{i=1}^{N}\varepsilon_{i}R_{U_{i}}\|_{\mathcal{A}} > c_{r}\log^{2}N(Nh)^{-1/2}\Big)$$
  
$$\leq \mathbb{P}\Big(\big\{\cap_{i}\mathcal{Q}_{i}\big\}\cap\big\{\|\frac{1}{N}\sum_{i=1}^{N}\varepsilon_{i}R_{U_{i}}\|_{\mathcal{A}} > c_{r}\log^{2}N(Nh)^{-1/2}\big\}\Big) + \mathbb{P}\big((\cap_{i}\mathcal{Q}_{i})^{c}\big)$$

(B.5)

$$\leq 2\exp(-\log^2 N) + 2N\exp(-\log^2 N) \to 0.$$

Therefore, we have  $\|\frac{1}{N}\sum_{i=1}^{N}\varepsilon_i R_{U_i}\| = o_P (\log^2 N(Nh)^{-1/2})$ . Moreover, by (A.26), we have  $\|P_{\lambda}m_0\|_{\mathcal{A}} = O(\lambda^{-1/2})$ . Furthermore, by Lemma 7.3, when s satisfies Condition (3.17), we have  $\|\frac{1}{s}\sum_{j=1}^{s} Rem^{(j)}\|_{\mathcal{A}} = o_P(s^{-1/2}b_{n,s}\log N)$ . By the definition of  $b_{n,s}$ , we have if s satisfies (3.18), then  $\|\frac{1}{s}\sum_{j=1}^{s} Rem^{(j)}\|_{\mathcal{A}} = o_P((Nh)^{-1/2})$ . Therefore, by (B.4), we have

$$\|\bar{m} - m_0\|_{\mathcal{A}} = o_P (\log^2 N(Nh)^{-1/2} + \lambda^{1/2}).$$

Hence we have

(B.6)  
$$\max_{1 \le j \le s} \| \frac{1}{\sqrt{n}} \sum_{i \in L_j} (\widehat{\Sigma}^{(j)})^{-1} X_i (f_0(Z_i) - \bar{f}(Z_i)) \|_2$$
$$= o_P (n^{1/2} h^{-1/2} (\log^2 N(Nh)^{-1/2} + \lambda^{1/2})).$$

Plugging the relationship n = N/s, we have when  $s \gtrsim h^{-2} \log^4 N$  and  $\lambda = O((Nh)^{-1})$ ,

$$\|\frac{1}{\sqrt{n}}\sum_{i\in L_j} \left(\widehat{\Sigma}^{(j)}\right)^{-1} X_i (f_0(Z_i) - \bar{f}(Z_i)) \|_2 = o_P(1)$$

Hence by (B.2) and (B.3),

$$\sqrt{n}(\dot{\boldsymbol{\beta}} - \boldsymbol{\beta}_0) \rightsquigarrow N(0, \sigma^2 \Sigma^{-1}),$$

as desired.

# 

#### B.2. Proof of Theorem 3.6.

**PROOF.** (i) By (7.3), we have for the *j*th sub-population

(B.7) 
$$\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_0^{(j)} = \frac{1}{n} \sum_{i \in L_j} L_{U_i} \varepsilon_i - L_{\lambda} f_0 - Rem_{\beta}^{(j)},$$

where  $Rem_{\beta}^{(j)} = 1/n \sum_{i \in L_j} \left( L_{U_i} \Delta m^{(j)}(U_i) - \mathbb{E}_U[L_U \Delta m^{(j)}(U)] \right)$ . Equation

(B.7) also holds for the k-th sub-population. Hence under  $H_0: \beta_0^{(j)} = \beta_0^{(k)}$ , we have

(B.8) 
$$\widehat{\boldsymbol{\beta}}^{(j)} - \widehat{\boldsymbol{\beta}}^{(k)} = \frac{1}{n} \sum_{i \in L_j} L_{U_i} \varepsilon_i - \frac{1}{n} \sum_{i \in L_k} L_{U_i} \varepsilon_i - (Rem_\beta^{(j)} - Rem_\beta^{(k)}),$$

By independence between two sub-populations, we have  $\frac{1}{n} \sum_{i \in L_j} L_{U_i} \varepsilon_i - \frac{1}{n} \sum_{i \in L_k} L_{U_i} \varepsilon_i \rightsquigarrow N(\mathbf{0}, 2\sigma^2 \Omega^{-1})$ . Moreover, when the conditions in Theorem 3.4 are satisfied, we have  $\sqrt{n} ||Q|| ||Rem_{\beta}^{(j)} - Rem_{\beta}^{(j)}||_2 = o_P(1)$  by triangular inequality. Therefore the result follows.

(ii) By (B.2), we have

(B.9) 
$$\sqrt{n}(\check{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_{0}^{(j)}) = \frac{1}{\sqrt{n}} (\widehat{\Sigma}^{(j)})^{-1} \sum_{i \in L_{j}} \boldsymbol{X}_{i} \varepsilon_{i} + \frac{1}{\sqrt{n}} (\widehat{\Sigma}^{(j)})^{-1} \sum_{i \in L_{j}} \boldsymbol{X}_{i} (f_{0}(Z_{i}) - \bar{f}(Z_{i})),$$

where  $\widehat{\Sigma}^{(j)} = \frac{1}{n} \sum_{i \in L_j} \mathbf{X}_i \mathbf{X}_i^T$ . The above equation is also true for k-th sub-population. So if s satisfies Condition (3.16), (3.17) and (3.18), we have

$$\left\|\frac{1}{\sqrt{n}}(\widehat{\Sigma}^{(j)})^{-1}\sum_{i\in L_j} X_i(f_0(Z_i) - \bar{f}(Z_i))\right\|_2 = o_P(1).$$

We have another equation that is same as (B.9) with j replaced by k. Hence subtracting the two equations, we have under  $H_0: \beta_0^{(j)} = \beta_0^{(k)}$ ,

$$\sqrt{n}(\check{\boldsymbol{\beta}}^{(j)} - \check{\boldsymbol{\beta}}^{(k)}) = \frac{1}{\sqrt{n}} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \sum_{i \in L_j} \boldsymbol{X}_i \varepsilon_i - \frac{1}{\sqrt{n}} (\widehat{\boldsymbol{\Sigma}}^{(k)})^{-1} \sum_{i \in L_k} \boldsymbol{X}_i \varepsilon_i + o_P(1).$$

Hence the conclusion follows from CLT and independence of sub-populations j and k.

**B.3. Proof of Theorem 3.7.** Before presenting the proof, we define the following preliminaries: for any  $\mathcal{G} \subset \{1, 2, \ldots, s\}$  with  $|\mathcal{G}| = d$ , let

$$T_{0,\mathcal{G}} := \max_{j \in \mathcal{G}, 1 \le k \le p} \frac{1}{\sqrt{n}} \sum_{i \in L_j} \left( \boldsymbol{\Sigma}^{-1} \right)_k \boldsymbol{X}_i \varepsilon_i,$$

where  $(\Sigma^{-1})_k$  denotes the *k*-th row of the precision matrix  $\Sigma^{-1}$  of X. Furthermore, let

$$W_{0,\mathcal{G}} := \max_{j \in \mathcal{G}, 1 \le k \le p} n^{-1/2} \sum_{i \in L_j} \Gamma_{i,k},$$

where  $\{\Gamma_i = (\Gamma_{i,1}, \dots, \Gamma_{i,p})\}$  for each  $i \in L_j$ ,  $j \in \mathcal{G}$  is a sequence of mean zero independent Gaussian vector with  $\mathbb{E}[\Gamma_i \Gamma_i^T] = (\Sigma)^{-1} \sigma^2$ . Lastly, it is useful to recall

$$W_{\mathcal{G}} := \max_{j \in \mathcal{G}, 1 \le k \le p} \frac{1}{\sqrt{n}} \sum_{i \in L_j} \left( \widehat{\boldsymbol{\Sigma}}^{(j)} \right)_k^{-1} \boldsymbol{X}_i e_i,$$

and  $c_{\mathcal{G}}(\alpha) = \inf\{t \in \mathbb{R} : \mathbb{P}(W_{\mathcal{G}} \le t \mid \mathbb{X}) \ge 1 - \alpha\}.$ 

The proof strategy is similar to that of Theorem 3.2 in Chernozhukov et al. (2013). Specifically, we first approximate  $T_{\mathcal{G}}$  by  $T_{0,\mathcal{G}}$ , and then apply Gaussian approximation to  $T_{0,\mathcal{G}}$  and  $W_{0,\mathcal{G}}$ . Then, we argue that  $W_{0,\mathcal{G}}$  and  $W_{\mathcal{G}}$  are close. Hence we can approximate the quantiles of  $T_{\mathcal{G}}$  by those of  $W_{\mathcal{G}}$ . The detailed proof is presented as follows.

**PROOF.** By (B.2), we have

(B.10) 
$$\sqrt{n}(\check{\boldsymbol{\beta}}^{(j)} - \widetilde{\boldsymbol{\beta}}^{(j)}) = n^{-1/2} \sum_{i \in L_j} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \boldsymbol{X}_i \varepsilon_i + \boldsymbol{\Delta}^{(j)},$$

where

$$\boldsymbol{\Delta}^{(j)} = n^{-1/2} \sum_{i \in L_j} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \boldsymbol{X}_i \big( f_0(Z_i) - \bar{f}(Z_i) \big).$$

By (B.6) in the proof of Theorem 3.5, we have

$$\max_{j \in \mathcal{G}} \| \boldsymbol{\Delta}^{(j)} \|_{\infty} = o_P \left( n^{1/2} h^{-1/2} (\log^2 N(Nh)^{-1/2} + \lambda^{1/2}) \right).$$

and when  $s \gtrsim h^{-2} \log(pd) \log^4 N$  and  $\lambda = O((Nh)^{-1})$ , we have

$$\max_{j \in \mathcal{G}} \|\boldsymbol{\Delta}^{(j)}\|_{\infty} = o_P(\log^{-1/2}(pd)).$$

By the definitions of  $T_{\mathcal{G}}$  and  $T_{0,\mathcal{G}}$  and (B.10), we have

$$|T_{\mathcal{G}} - T_{0,\mathcal{G}}| \le \max_{j \in \mathcal{G}} \frac{1}{\sqrt{n}} \Big\| \sum_{i \in L_j} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \boldsymbol{X}_i \varepsilon_i - \boldsymbol{\Sigma}^{-1} \boldsymbol{X}_i \varepsilon_i \Big\|_{\infty} + \max_{j \in \mathcal{G}} \|\boldsymbol{\Delta}^{(j)}\|_{\infty},$$

where we used the fact that  $\max_j a_j - \max_j b_j \leq \max_j |a_j - b_j|$  for any two finite sequences  $\{a_j\}, \{b_j\}$ . By the above inequality and Lemma B.2, there exist  $\zeta_1$  and  $\zeta_2$  such that

(B.11) 
$$\mathbb{P}(|T_{\mathcal{G}} - T_{0,\mathcal{G}}| \ge \zeta_1) \le \zeta_2,$$

where  $\zeta_1 \sqrt{1 \vee \log(pd/\zeta_1)} = o(1)$  and  $\zeta_2 = o(1)$ .

We next turn to bound the distance between quantiles of  $W_{\mathcal{G}}$  and  $W_{0,\mathcal{G}}$ . Let  $c_{0,\mathcal{G}}(\alpha) := \inf\{t \in \mathbb{R} : \mathbb{P}(W_{0,\mathcal{G}} \leq t) \geq 1 - \alpha\}$ , and let  $\pi(\nu) := C_2 \nu^{1/3} (1 \vee \log(pd/\nu))^{2/3}$  with  $C_2 > 0$ , and

$$\Psi := \max_{\substack{1 \leq k, \ell \leq p \ j \in \mathcal{G}}} \sigma^2 |(\widehat{\mathbf{\Sigma}}^{(j)} - \mathbf{\Sigma})_{k\ell}|.$$

As the data size in each  $L_j$  is the same, we can relabel  $\{\mathbf{X}_i \in \mathbb{R}^p\}_{i \in L_j, j \in \mathcal{G}}$  as  $\{\mathbf{X}_i^{(j)} \in \mathbb{R}^p\}_{1 \leq i \leq n, j \in \mathcal{G}}$  and  $\{\Gamma_i \in \mathbb{R}^p\}_{1 \leq i \leq n, j \in \mathcal{G}}$ . Then we can re-write  $W_{0,\mathcal{G}} = \max_{j \in \mathcal{G}, 1 \leq k \leq p} U_k^{(j)}$ , and  $W_{\mathcal{G}} = \max_{j \in \mathcal{G}, 1 \leq k \leq p} V_k^{(j)}$ , where

$$U_k^{(j)} = \frac{1}{\sqrt{n}} \sum_{i=1}^n \Gamma_{ik}^{(j)} \quad \text{and} \quad V_k^{(j)} = \frac{1}{\sqrt{n}} \sum_{i=1}^n (\widehat{\boldsymbol{\Sigma}}^{(j)})_k^{-1} \boldsymbol{X}_i^{(j)} e_i^{(j)}.$$

 $(e_i^{(j)}$  is defined in the similar way). Notice that  $U = \{U_k^{(j)}\}_{1 \le k \le p, j \in \mathcal{G}}$  can be viewed as an  $(p \cdot d)$ -dimensional Gaussian random vector with mean zero and covariance

$$\begin{pmatrix} \sigma^{2} \mathbf{\Sigma}^{-1} & 0 & \dots & 0 \\ 0 & \sigma^{2} \mathbf{\Sigma}^{-1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma^{2} \mathbf{\Sigma}^{-1} \end{pmatrix} \in \mathbb{R}^{(p \cdot d) \times (p \cdot d)}.$$

Conditioned on  $\mathbb{X}$ ,  $\mathbf{V} = \{V_k^{(j)}\}_{1 \le k \le p, j \in \mathcal{G}}$  can be viewed as an  $(p \cdot d)$ -dimensional Gaussian random vector with mean zero and covariance

$$\begin{pmatrix} \sigma^2(\widehat{\mathbf{\Sigma}}^{(1)})^{-1} & 0 & \dots & 0\\ 0 & \sigma^2(\widehat{\mathbf{\Sigma}}^{(2)})^{-1} & \dots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \dots & \sigma^2(\widehat{\mathbf{\Sigma}}^{(d)})^{-1} \end{pmatrix} \in \mathbb{R}^{(p \cdot d) \times (p \cdot d)}.$$

Using Gaussian comparison (Lemma 3.1 in Chernozhukov et al. (2013)) and applying the same argument as in the proof of Lemma 3.2 in Chernozhukov et al. (2013), we obtain for any  $\nu > 0$ 

(B.12) 
$$\mathbb{P}(c_{0,\mathcal{G}}(\alpha) \le c_{\mathcal{G}}(\alpha + \pi(\nu))) \ge 1 - \mathbb{P}(\Psi > \nu),$$

(B.13) 
$$\mathbb{P}(c_{\mathcal{G}}(\alpha) \le c_{0,\mathcal{G}}(\alpha + \pi(\nu))) \ge 1 - \mathbb{P}(\Psi > \nu)$$

By Lemma B.1, we have

(B.14) 
$$\sup_{\alpha \in (0,1)} \left| \mathbb{P}(T_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha)) - \alpha \right| \leq \sup_{\alpha \in (0,1)} \left| \mathbb{P}(W_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha)) - \alpha \right| + n^{-c}.$$

To further control  $\mathbb{P}(W_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha))$ , we define  $\mathcal{E}_1 = \{c_{0,\mathcal{G}}(\alpha - \pi(\nu)) \leq c_{\mathcal{G}}(\alpha)\}, \mathcal{E}_2 = \{c_{\mathcal{G}}(\alpha) \leq c_{0,\mathcal{G}}(\alpha + \pi(\nu))\}$ . We have

$$\mathbb{P}(W_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha)) = \mathbb{P}(W_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha), \mathcal{E}_{1}) + \mathbb{P}(W_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha), \mathcal{E}_{1}^{c})$$
  
$$\leq \mathbb{P}(W_{0,\mathcal{G}} > c_{0,\mathcal{G}}(\alpha - \pi(\nu))) + \mathbb{P}(\mathcal{E}_{1}^{c})$$
  
$$\leq \alpha - \pi(\nu) + \mathbb{P}(\Psi > \nu),$$

where the last inequality is by the definition of  $c_{0,\mathcal{G}}(\alpha)$  and (B.12). Similarly,

we have

$$\mathbb{P}(W_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha)) = 1 - \mathbb{P}(W_{0,\mathcal{G}} \le c_{\mathcal{G}}(\alpha))$$
  
= 1 - \mathbb{P}(W\_{0,\mathcal{G}} \le c\_{\mathcal{G}}(\alpha), \mathcal{E}\_2) - \mathbb{P}(W\_{0,\mathcal{G}} \le c\_{\mathcal{G}}(\alpha), \mathcal{E}\_2^c)  
\ge 1 - \mathbb{P}(W\_{0,\mathcal{G}} \le c\_{0,\mathcal{G}}(\alpha + \pi(\nu))) - \mathbb{P}(\mathcal{E}\_2^c)  
\ge \alpha + \pi(\nu) - \mathbb{P}(\mathbb{V} > \nu),

where the last inequality is by the definition of  $c_{0,\mathcal{G}}(\alpha)$  and (B.13). Hence it follows from (B.14) that

(B.15) 
$$\sup_{\alpha \in (0,1)} \left| \mathbb{P}(T_{0,\mathcal{G}} > c_{\mathcal{G}}(\alpha)) - \alpha \right| \le \pi(\nu) + \mathbb{P}(\Psi > \nu) + n^{-c}.$$

Define the event  $\mathcal{E}_3 = \{ |T_{0,\mathcal{G}} - T_{\mathcal{G}}| \leq \zeta_1 \}$ . By (B.11), we have  $\mathbb{P}(\mathcal{E}_3^c) \leq \zeta_2$ . Hence, we deduce that for any  $\alpha$ 

$$\mathbb{P}(T_{\mathcal{G}} \ge c_{G}(\alpha)) - \alpha \le \mathbb{P}(T_{\mathcal{G}} \ge c_{G}(\alpha), \mathcal{E}_{3}) + \mathbb{P}(\mathcal{E}_{3}^{c}) - \alpha$$
  
$$\le \mathbb{P}(T_{0,\mathcal{G}} \ge c_{G}(\alpha) - \zeta_{1}) + \zeta_{2} - \alpha,$$
  
$$\le \mathbb{P}(T_{0,\mathcal{G}} \ge c_{G}(\alpha)) + C\zeta_{1}\sqrt{1 \lor \log(ps/\zeta_{1})} + \zeta_{2} - \alpha$$
  
$$\le \pi(\nu) + \mathbb{P}(\Psi > \nu) + n^{-c} + C\zeta_{1}\sqrt{1 \lor \log(ps/\zeta_{1})} + \zeta_{2},$$

where the second last inequality is by Corollary 16 of Wasserman (2014) (Gaussian anti-concentration). By similar arguments, we get the same bound for  $\alpha - \mathbb{P}(T_{\mathcal{G}} \geq c_G(\alpha))$ , so we have

$$\sup_{\alpha} \left| \mathbb{P}(T_{\mathcal{G}} \ge c_G(\alpha)) - \alpha \right| \le \pi(\nu) + \mathbb{P}(\Psi > \nu) + n^{-c} + C\zeta_1 \sqrt{1 \vee \log(pd/\zeta_1)} + \zeta_2.$$

Lastly, we bound  $\Psi$ . By (B.18) in the proof of Lemma B.2 and the fact that elementwise infinity norm is bounded by spectral norm, we obtain

$$\Psi \leq \max_{j \in \mathcal{G}} \|\widehat{\mathbf{\Sigma}}^{(j)} - \mathbf{\Sigma}\|_{\infty} = o_P \Big( p \sqrt{(\log d)/n} \Big).$$

Hence, choosing  $\nu = p\sqrt{(\log d)/n}$ , we get

$$\sup_{\alpha} \left| \mathbb{P}(T_{\mathcal{G}} \ge c_G(\alpha)) - \alpha \right| = o(1),$$

which concludes the proof.

**Lemma B.1.** Suppose Assumption 3.1 holds. For any  $\mathcal{G} \subset \{1, 2, ..., s\}$  with d = d, if  $(\log(pdn))^7/n \leq C_1 n^{-c_1}$  for some constants  $c_1, C_1 > 0$ , then we have

$$\sup_{x \in \mathbb{R}} \left| \mathbb{P} \big( T_{0,\mathcal{G}} \le x \big) - \mathbb{P} \big( W_{0,\mathcal{G}} \le x \big) \right| \le n^{-c},$$

for some constant c > 0.

**PROOF.** As the data size in each  $L_j$  is the same, we can relabel  $\{X_i \in X_i \in X_i\}$ 

 $\mathbb{R}^{p}_{i \in L_{j}, j \in \mathcal{G}} \text{ as } \{ \boldsymbol{X}_{i}^{(j)} \in \mathbb{R}^{p}_{i \leq i \leq n, j \in \mathcal{G}}. \text{ Then } T_{0,\mathcal{G}} = \max_{j \in \mathcal{G}, 1 \leq k \leq p} n^{-1/2} \sum_{i=1}^{n} \xi_{ik}^{(j)}, \text{ where } \xi_{ik}^{(j)} = (\boldsymbol{\Sigma}^{-1})_{k} \boldsymbol{X}_{i}^{(j)} \varepsilon_{i}. \text{ For each } i, \{\xi_{ik}^{(j)}\}_{1 \leq k \leq p, j \in \mathcal{G}} \text{ can be viewed as a } (p \cdot d) \text{-dimensional vector with covariance matrix}$ 

$$\begin{pmatrix} \sigma^{2} \mathbf{\Sigma}^{-1} & 0 & \dots & 0 \\ 0 & \sigma^{2} \mathbf{\Sigma}^{-1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma^{2} \mathbf{\Sigma}^{-1} \end{pmatrix} \in \mathbb{R}^{(p \cdot d) \times (p \cdot d)}.$$

The same thing can be done for  $\Gamma$  which results in the same covariance matrix. Then we apply Corollary 2.1 of Chernozhukov et al. (2013) to prove the Gaussian approximation result stated in the lemma. It suffices to verify Condition (E1) therein. We have  $\mathbb{E}[(\xi_{ik}^{(j)})^2] = (\Sigma^{-1})_{kk}$  is a constant, and  $\max_{\ell=1,2} \mathbb{E}[|\xi_{ik}^{(j)}|^{2+\ell}/B^{\ell}] + \mathbb{E}[\exp(|\xi_{ik}^{(j)}|/B)] \leq 4$  for some large enough constant *B*, by the sub-Gaussianity of  $\varepsilon_i^{(j)}$  and the boundedness of  $X_i^{(j)}$ . Hence Condition (E1) is verified, and by the assumption that  $(\log(pdn))^7/n \leq C_1 n^{-c_1}$ , we get the desired result.

**Lemma B.2.** Suppose Assumption 3.1 holds. For any  $\mathcal{G} \subset \{1, 2, \ldots, s\}$  with d = d, suppose  $p^2 \log(pd)/\sqrt{n} = o(1)$ . Then there exist  $\zeta_1$  and  $\zeta_2$  such that

$$\mathbb{P}\left(\max_{j\in\mathcal{G}}\frac{1}{\sqrt{n}}\left\|\sum_{i\in L_{j}}(\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1}\boldsymbol{X}_{i}\varepsilon_{i}-\boldsymbol{\Sigma}^{-1}\boldsymbol{X}_{i}\varepsilon_{i}\right\|_{\infty}>\zeta_{1}\right)\leq\zeta_{2},$$

where  $\zeta_1 \sqrt{1 \vee \log(pd/\zeta_1)} = o(1)$  and  $\zeta_2 = o(1)$ .

PROOF. We have

(B.16)  

$$\max_{j \in \mathcal{G}} \frac{1}{\sqrt{n}} \left\| \sum_{i \in L_j} (\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i \varepsilon_i - \boldsymbol{\Sigma}^{-1} \boldsymbol{X}_i \varepsilon_i \right\|_{\infty} \\
\leq \max_{j \in \mathcal{G}} \left\| (\widehat{\Sigma}^{(j)})^{-1} - \boldsymbol{\Sigma}^{-1} \right\|_1 \max_{j \in \mathcal{G}} \left\| \frac{1}{\sqrt{n}} \sum_{i \in L_j} \boldsymbol{X}_i \varepsilon_i \right\|_{\infty} \\
\leq \max_{j \in \mathcal{G}} p \left\| (\widehat{\Sigma}^{(j)})^{-1} - \boldsymbol{\Sigma}^{-1} \right\| \max_{j \in \mathcal{G}} \left\| \frac{1}{\sqrt{n}} \sum_{i \in L_j} \boldsymbol{X}_i \varepsilon_i \right\|_{\infty},$$

where  $\|\cdot\|_1$  denotes the elementwise  $L_1$  norm of matrices. As  $\varepsilon_i$  are i.i.d. sub-Gaussian random variables, we have by Hoeffding's inequality that for

any  $j \in \mathcal{G}$  and  $1 \leq k \leq p$ 

$$\mathbb{P}\Big(\frac{1}{\sqrt{n}}\sum_{i\in L_j}X_{ik}\varepsilon_i > t \,|\,\mathbb{X}\Big) \le \exp\Big(-\frac{nt^2}{\sum_{i\in L_j}X_{ik}^2\sigma^2}\Big)$$
$$\le \exp\Big(-\frac{t^2}{c_x^2\sigma^2}\Big),$$

where the second inequality is by the boundedness of  $X_{ik}$ . By law of iterated expectation and union bound we have

$$\mathbb{P}\Big(\max_{j\in\mathcal{G}}\left\|\frac{1}{\sqrt{n}}\sum_{i\in L_j}\boldsymbol{X}_i\varepsilon_i\right\|_{\infty} > t\Big) \le pd\exp\Big(-\frac{t^2}{c_x^2\sigma^2}\Big).$$

Letting  $t = 2c_x \sigma \sqrt{\log(pd)}$ , we get with probability at least  $1 - (pd)^{-1}$  that

(B.17) 
$$\max_{j \in \mathcal{G}} \left\| \frac{1}{\sqrt{n}} \sum_{i \in L_j} \boldsymbol{X}_i \varepsilon_i \right\|_{\infty} \le 2c_x \sigma \sqrt{\log(pd)}.$$

By the boundedness of  $\boldsymbol{X}$ , we have  $\|\boldsymbol{X}_i \boldsymbol{X}_i^T - \mathbb{E}[\boldsymbol{X}_i \boldsymbol{X}_i^T]\| \leq 2\|\boldsymbol{X}_i \boldsymbol{X}_i^T\| \leq 2\|\boldsymbol{X}_i \boldsymbol{X}_i^T\| \leq 2\|\boldsymbol{X}_i \|_2^2 \leq 2pc_x^2$ . Therefore, by Lemma G.3, we have for all  $j \in \mathcal{G}$  that

$$\mathbb{P}\Big(\|\widehat{\boldsymbol{\Sigma}}^{(j)} - \boldsymbol{\Sigma}\| \ge t\Big) \le \mathbb{P}\Big(\left\|\frac{1}{n}\sum_{i\in L_j}\boldsymbol{X}_i\boldsymbol{X}_i^T - \mathbb{E}[\boldsymbol{X}_i\boldsymbol{X}_i^T\| \ge t\Big) \\ \le p\exp\Big(-\frac{nt^2}{32p^2c_x^4}\Big).$$

and so it follows from union bound that

$$\mathbb{P}\Big(\max_{j\in\mathcal{G}}\|\widehat{\boldsymbol{\Sigma}}^{(j)}-\boldsymbol{\Sigma}\|\geq t\Big)\leq pd\exp\Big(-\frac{nt^2}{32p^2c_x^4}\Big).$$

Choosing  $t = 64p\sqrt{(\log d)/n}$ , we obtain

(B.18) 
$$\max_{j \in \mathcal{G}} \|\widehat{\boldsymbol{\Sigma}}^{(j)} - \boldsymbol{\Sigma}\| = o_P \Big( p \sqrt{\frac{\log d}{n}} \Big).$$

Thus, by Lemma G.4, we get

(B.19) 
$$\max_{j \in \mathcal{G}} \|(\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} - \boldsymbol{\Sigma}^{-1}\| = o_P \left( p \sqrt{\frac{\log d}{n}} \right).$$

Combining (B.16), (B.17) and (B.19), we have

$$\max_{j \in \mathcal{G}} \frac{1}{\sqrt{n}} \Big\| \sum_{i \in L_j} (\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1} \boldsymbol{X}_i \varepsilon_i - \boldsymbol{\Sigma}^{-1} \boldsymbol{X}_i \varepsilon_i \Big\|_{\infty} = o_P \Big( p^2 \frac{\log(pd)}{\sqrt{n}} \Big)$$

We choose  $\zeta_1$  such that  $p^2 \log(pd)/(\sqrt{n}\zeta_1) = o(1)$  and  $\zeta_1 \sqrt{1 \vee \log(pd/\zeta_1)} = o(1)$ 

o(1), e.g.,  $\zeta_1^2 = p^2 \log(pd)/\sqrt{n}.$  Then by the above equation we have

$$\mathbb{P}\left(\max_{j\in\mathcal{G}}\frac{1}{\sqrt{n}}\Big\|\sum_{i\in L_j}(\widehat{\boldsymbol{\Sigma}}^{(j)})^{-1}\boldsymbol{X}_i\varepsilon_i-\boldsymbol{\Sigma}^{-1}\boldsymbol{X}_i\varepsilon_i\Big\|_{\infty}\geq\zeta_1\right)<\zeta_2,$$

where  $\zeta_2 = o(1)$ .

#### APPENDIX C: PROOFS IN SECTION 4

#### C.1. Proof of Corollary 4.1.

PROOF. We begin by computing h. As  $\mu_i = 0$  for i > r, we have that  $h^{-1} = \sum_{i=1}^r \frac{1}{1+\lambda/\mu_i} \asymp r$ . Hence  $h \asymp r^{-1}$ .

Therefore by Theorem 3.4,  $\lambda = o((Nh)^{-1/2} \wedge n^{-1/2}) = o(N^{-1/2})$ . We next calculate the asymptotic covariance.

$$\begin{aligned} A_k(z_0) &= \langle A_k, \widetilde{K}_{z_0} \rangle_{\mathcal{C}} = \langle B_k, \widetilde{K}_{z_0} \rangle_{L_2(\mathbb{P}_Z)} \\ &= \sum_{i=1}^r \frac{\langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)}}{1 + \frac{\lambda}{\mu_i}} \phi_i(z_0) \to \sum_{i=1}^r \langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)} \phi_i(z_0) \end{aligned}$$

Hence  $\gamma_{z_0} = h^{1/2} \sum_{i=1}^r \langle B_k, \phi_i \rangle_{L_2(\mathbb{P}_Z)} \phi_i(z_0)$ . The formula for  $\Sigma_{12}^*$  and  $\Sigma_{22}^*$  then follows from Theorem 3.4.

We next calculate the entropy integral  $\omega(\mathcal{F}, \delta)$  for finite rank RKHS and the upper bound for s. Define  $\widetilde{\mathcal{F}}_2 = \{f \in \mathcal{H} : \|f\|_{\sup} \leq 1, \|f\|_{\mathcal{H}} \leq 1\}$ . By Carl and Triebel (1980), for finite rank RKHS,

$$\log \mathcal{N}(\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, \delta) \asymp r \log \delta^{-1}.$$

We have that  $\mathcal{N}(\mathcal{F}, \|\cdot\|_{\sup}, \delta) \leq \mathcal{N}(\mathcal{F}_1, \|\cdot\|_{\sup}, \delta)\mathcal{N}(\mathcal{F}_2, \|\cdot\|_{\sup}, \delta)$ . As  $\mathcal{N}(\mathcal{F}_1, \|\cdot\|_{\sup}, \delta)$  is dominated by  $\mathcal{N}(\mathcal{F}_2, \|\cdot\|_{\sup}, \delta)$ , it suffices to bound  $\mathcal{N}(\mathcal{F}_2, \|\cdot\|_{\sup}, \delta)$ . Now by Van Der Vaart and Wellner (1996), we have that

$$\begin{split} \mathcal{N}(\mathcal{F}_2, \|\cdot\|_{\sup}, \delta) &\leq \mathcal{N}(h^{1/2}\lambda^{-1/2}\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, \delta) \\ &= \mathcal{N}(\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, h^{-1/2}\lambda^{1/2}\delta). \end{split}$$

Hence

$$\begin{split} \omega(\mathcal{F}, \delta) &\leq \int_0^\delta \sqrt{\log \mathcal{N}(\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, h^{-1/2}\lambda^{1/2}\varepsilon)} d\varepsilon \\ &\asymp \int_0^\delta \sqrt{r \log(h^{1/2}\lambda^{-1/2}\varepsilon^{-1})} d\varepsilon \\ &\asymp \sqrt{r} \delta \sqrt{\log(h^{1/2}\lambda^{-1/2}\delta^{-1})} \end{split}$$

Now we are ready to calculate the upper bound for s. We plug in n = N/sand  $h \approx r^{-1}$  into (3.6) and (3.7), and by the condition  $\lambda = o\left(\frac{1}{\sqrt{N}}\right)$ , we get  $s = o\left(\frac{N}{\sqrt{\log \lambda^{-1} \log^6 N}}\right)$ . This upper bound needs to allow the case that s = 1, which yields the lower bound for  $\lambda$ :  $\sqrt{\log(\lambda^{-1})} = o\left(N \log^{-6} N\right)$ .

#### C.2. Proof of Corollary 4.2.

PROOF. Recall that we have  $h \simeq r^{-1}$ . To optimize the rate, we choose  $\lambda$  such that  $\frac{1}{Nh} \simeq \lambda$ , which yields  $\lambda = \frac{r}{N}$ . By Theorem 3.1 we have

$$\mathbb{E}\left[\|\bar{f}_{N,\lambda} - f_0\|_{L_2(\mathbb{P}_Z)}^2\right] \le Cr/N + s^{-1}a(n,s,h,\lambda,\omega).$$

For the remainder term to be small, we need  $s^{-1}a(n, s, h, \lambda, \omega) \lesssim N^{-1}$ . Plugging in  $a(n, s, h, \lambda, \omega)$ , h and  $\lambda$ , we get the upper bound for s.  $\Box$ 

### C.3. A Lemma for Exponentially Decaying RKHS.

**Lemma C.1.** Let  $h = (-\log \lambda)^{-1/p}$ . For all  $t > 0, p \ge 1$  and some positive constants  $c, \alpha$ , we have

$$\lim_{\lambda \to 0} \sum_{\ell=1}^{\infty} \frac{1}{(1 + \lambda c \exp(\alpha \ell^p))^t} = \alpha^{-1/p}.$$

PROOF. We have by convexity that

$$\sum_{\ell=1}^{\infty} \frac{1}{(1+\lambda c \exp(\alpha \ell^p))^t} \le \int_0^{\infty} \frac{1}{(1+\lambda c \exp(\alpha x^p))^t} dx$$

We then approximate the integral by

$$\int_{0}^{\infty} \frac{dx}{(1+\lambda c \exp(\alpha x^{p}))^{t}}$$

$$= \int_{0}^{(\alpha^{-1}\log(1/\lambda))^{1/p}} \frac{dx}{(1+\lambda c \exp(\alpha x^{p}))^{t}}$$

$$+ \int_{(\alpha^{-1}\log(1/\lambda))^{1/p}}^{\infty} \frac{dx}{(1+\lambda c \exp(\alpha x^{p}))^{t}}$$

$$\leq (\alpha^{-1}\log(1/\lambda))^{1/p} + \int_{(\alpha^{-1}\log(1/\lambda))^{1/p}}^{\infty} (c\lambda)^{-t} \exp(-t\alpha x^{p}) dx$$
(C.1)
$$= (\alpha^{-1}\log(1/\lambda))^{1/p} + o(1),$$

where the last equality is by L'Hospital's Rule for  $\lambda \to 0$ .

Moreover, we have for any  $\epsilon \in (0, 1)$  that

$$\sum_{\ell=1}^{\infty} \frac{1}{(1+\lambda c \exp(\alpha \ell^p))^t} \ge \int_1^{\infty} \frac{1}{(1+\lambda c \exp(\alpha x^p))^t} dx$$
$$\ge \int_1^{(\epsilon \alpha^{-1} \log(1/\lambda))^{1/p}} \frac{1}{(1+\lambda c \exp(\alpha x^p))^t} dx$$
$$\ge \frac{1}{(1+c\lambda^{1-\epsilon})^t} \Big( (\epsilon \alpha^{-1} \log(1/\lambda))^{1/p} - 1 \Big)$$
$$= \frac{1}{(1+c\lambda^{1-\epsilon})^t} \Big( (\epsilon \alpha^{-1} \log(1/\lambda))^{1/p} \Big) + O(1).$$

Combining (C.1) and (C.2), we get

$$\left(\frac{\epsilon}{\alpha}\right)^{1/p} \le \lim_{\lambda \to 0} \sum_{\ell=1}^{\infty} \frac{h}{(1 + \lambda c \exp(\alpha \ell^p))^t} \le \left(\frac{1}{\alpha}\right)^{1/p}$$

for any  $\epsilon \in (0, 1)$ . Lastly, letting  $t \to 1$ , we get the desired result.

#### 

## C.4. Proof the Corollary 4.3.

PROOF. As before, we start by calculating h. By Lemma C.1 with t = 1, we have  $h \asymp (-\log \lambda/c)^{-1/p}$ .

As  $h \to 0$ , Theorem 3.4 shows that  $\alpha_{z_0} = \gamma_{z_0} = 0$ . Moreover,

$$|W_{\lambda}f_{0}(z_{0})| = \lambda |\sum_{\ell=1}^{\infty} \frac{\theta_{\ell}}{\lambda + \mu_{\ell}} \phi_{\ell}(z_{0})|$$
$$\leq \lambda \sum_{\ell=0}^{\infty} |\phi_{\ell}(z_{0})\langle f_{0}, \phi_{\ell}\rangle_{\mathcal{H}}| = O(\lambda).$$

Therefore, by Theorem 3.4, we can completely remove the asymptotic bias by choosing  $\lambda = o((Nh)^{-1/2} \wedge n^{-1/2}) = o(N^{-1/2} \log^{1/(2p)} N \wedge n^{-1/2})$ . We next calculate the entropy integral. We have that for RKHS with exponentially decaying eigenvalues, by Proposition 17 in Williamson et al. (2001) with p = 2,

$$\log \mathcal{N}(\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, \delta) \asymp \left(\log \frac{1}{\delta}\right)^{\frac{p+1}{p}}.$$

Then following the deduction in the proof of Corollary 4.1, we have

$$\begin{split} \omega(\delta) &\leq \int_0^\delta \sqrt{\log(1 + \mathcal{N}(\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, (c_r^{-2}h\lambda^{-1})^{-1/2}\varepsilon))} d\varepsilon \\ &\approx \int_0^\delta \sqrt{\left(\log\frac{1}{(c_r^{-2}h\lambda^{-1})^{-1/2}\varepsilon}\right)^{\frac{p+1}{p}}} d\varepsilon \\ &\approx \delta \log^{\frac{p+1}{2p}} (h^{1/2}\lambda^{-1/2}\delta^{-1}). \end{split}$$

For the range on s, we plug in n = N/s and  $h \asymp (-\log \lambda/c)^{-1/p}$  into (3.6) and (3.7), and we get that it suffices to take

$$s = o\left(\frac{N}{\log^6 N \log^{(p+4)/p} \lambda^{-1}}\right).$$

Again the upper bound must allow the case that s = 1, which yields the lower bound for the choice of  $\lambda$ .

## C.5. Proof of Corollary 4.4.

PROOF. Recall that we have  $h \simeq (-\log \lambda/c)^{-1/p}$ . To balance variance and bias, we choose  $\lambda = \frac{(\log N)^{1/p}}{N}$ . By Theorem 3.1 we have

$$\mathbb{E}\left[\|\bar{f}_{N,\lambda} - f_0\|_{L_2(\mathbb{P}_Z)}^2\right] \le C(\log N)^{1/p}/N + s^{-1}a(n,s,h,\lambda,\omega).$$

For the remainder term to be small, we need  $s^{-1}a(n, s, h, \lambda, \omega) \lesssim (\log N)^{1/p}/N$ . Plugging in  $h, \lambda$  and  $\omega(\mathcal{F}, 1)$ , we get the upper bound for s.  $\Box$ 

#### C.6. Proof of Corollary 4.5.

PROOF. Again, we begin by calculating h. As  $\mu_j \leq c j^{-2\nu}$ , we approximate h using integration. For simplicity, let c = 1 here. We have

$$h^{-1} \le \int_0^\infty \frac{1}{1 + \lambda x^{2\nu}} dx = \int_0^{\lambda^{-\frac{1}{2\nu}}} \frac{1}{1 + \lambda x^{2\nu}} dx + \int_{\lambda^{-\frac{1}{2\nu}}}^\infty \frac{1}{1 + \lambda x^{2\nu}} dx$$
$$\le \left(1 + \frac{1}{1 - 2\nu}\right) \lambda^{-\frac{1}{2\nu}}.$$

On the other hand, we also have

$$h^{-1} \ge \int_{1}^{\infty} \frac{1}{1 + \lambda x^{2\nu}} dx = \int_{1}^{\lambda^{-\frac{1}{2\nu}}} \frac{1}{1 + \lambda x^{2\nu}} dx + \int_{\lambda^{-\frac{1}{2\nu}}}^{\infty} \frac{1}{1 + \lambda x^{2\nu}} dx$$
$$\ge \left(2 + \frac{1}{2 - 4\nu}\right) \lambda^{-\frac{1}{2\nu}}.$$

Hence we conclude that  $h^{-1} \asymp \lambda^{-\frac{1}{2\nu}}$  and thus  $h \asymp \lambda^{\frac{1}{2\nu}}$ .

As  $h \to 0$ , Theorem 3.4 shows that  $\alpha_{z_0} = \gamma_{z_0} = 0$ . Similar to proof of Corollary 4.3, we get  $|W_{\lambda}f_0(z_0)| = o(\lambda)$ , and by Theorem 3.4, we can remove the asymptotic bias by choosing  $\lambda = o((Nh)^{-1/2} \wedge n^{-1/2}) = o(N^{-\frac{2\nu}{4\nu+1}} \wedge n^{-1/2})$ . We next calculate the entropy integral. We have that for RKHS with polynomially decaying eigenvalues, by Proposition 16 in Williamson et al. (2001),

$$\log \mathcal{N}(\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, \delta) \asymp \left(\frac{1}{\delta}\right)^{\frac{1}{\nu}}.$$

Then following the deduction in the proof of Corollary 4.1, we have

$$\begin{split} \omega(\mathcal{F}, \delta) &\leq \int_0^\delta \sqrt{\log \mathcal{N}(\widetilde{\mathcal{F}}_2, \|\cdot\|_{\sup}, h^{-1/2}\lambda^{1/2}\varepsilon)} d\varepsilon \\ &\asymp \int_0^\delta \sqrt{\left(\frac{1}{h\lambda^{-1})^{-1/2}\varepsilon}\right)^{\frac{1}{\nu}}} d\varepsilon \\ &\asymp (h\lambda^{-1})^{\frac{1}{4\nu}} \delta^{1-\frac{1}{2\nu}}. \end{split}$$

For the range on s, we plug in n = N/s and  $h \simeq \lambda^{\frac{1}{2\nu}}$  into (3.6) and (3.7), and it follows that s needs to satisfy

$$s = o\left(\lambda^{\frac{10\nu-1}{4\nu^2}} N \log^{-6} N\right).$$

Again the upper bound must allow the case that s = 1, which yields the lower bound for the choice of  $\lambda$ :  $\lambda^{-1} = o(N^{\frac{4\nu^2}{10\nu-1}})$ .

### C.7. Proof of Corollary 4.6.

PROOF. Recall that we have  $h \simeq \lambda^{1/2\nu}$ . To optimize the rate, we choose  $\lambda$  such that  $\frac{1}{Nh} \simeq \lambda$ , which yields  $\lambda = N^{-\frac{2\nu}{2\nu+1}}$ . By Theorem 3.1 we have

$$\mathbb{E}\left[\|\bar{f}_{N,\lambda} - f_0\|_{L_2(\mathbb{P}_Z)}^2\right] \le CN^{-\frac{2\nu}{2\nu+1}} + s^{-1}a(n,s,h,\lambda,\omega)$$

For the remainder term to be small, we need  $s^{-1}a(n, s, h, \lambda, \omega) \leq N^{-\frac{2\nu}{2\nu+1}}$ . Plugging in  $a_n, h$  and  $\lambda$ , we get the upper bound for s.

**C.8. Proof of Lemma 4.1.** Recall that  $\lambda = h^{2\nu}$ . By Theorem 3.3 for the asymptotic variance, we compute that

$$\begin{split} h\|\widetilde{K}_{z_0}\|_{L_2(\mathbb{P}_Z)}^2 &= h \sum_{\ell=1}^{\infty} \left(\frac{\phi_{\ell}(z_0)}{1+\lambda/\mu_{\ell}}\right)^2 \\ &= h\left(1 + \sum_{\ell=1}^{\infty} \frac{2\cos^2(2\ell\pi z_0) + 2\sin^2(2\ell\pi z_0)}{(1+\lambda(2\ell\pi)^{2\nu})^2}\right) \\ &= h\left(1 + \sum_{\ell=1}^{\infty} \frac{2}{(1+(2\ell\pi h)^{2\nu})^2}\right) \end{split}$$

And we have that

$$\sum_{\ell=0}^{\infty} \frac{2\pi h}{(1+(2\ell\pi h)^{2\nu})^2} \leq \sum_{\ell=1}^{\infty} \int_{2\pi h(\ell-1)}^{2\pi h\ell} \frac{1}{(1+x^{2\nu})^2} dx$$
$$\to \int_{0}^{\infty} \frac{1}{(1+x^{2\nu})^2} dx$$

and similarly

$$\sum_{\ell=1}^{\infty} \frac{2\pi h}{(1+(2\ell\pi h)^{2\nu})^2} \geq \sum_{\ell=1}^{\infty} \int_{2\pi h(\ell-1)}^{2\pi h\ell} \frac{1}{(1+x^{2\nu})^2} dx$$
$$\to \int_{0}^{\infty} \frac{1}{(1+x^{2\nu})^2} dx$$

The two inequalities yield

$$h \| \widetilde{K}_{z_0} \|_{L_2(\mathbb{P}_Z)}^2 \to \int_0^\infty \frac{1}{\pi (1 + x^{2\nu})^2} dx$$

and so

(C.3) 
$$\sigma_{z_0}^2 = \int_0^\infty \frac{1}{\pi (1+x^{2\nu})^2} dx.$$

## APPENDIX D: PROOF OF RESULTS IN SECTION 5

## D.1. Proof of Proposition 5.1.

PROOF. The proof follows similarly as the proof for Theorem 3.1.  $\hfill \Box$ 

## D.2. Proof of Proposition 5.2.

PROOF. Recall (7.2) from proof of Theorem 3.1 in Section 7.2

$$\widehat{m}^{(j)} - m_0 = \frac{1}{n} \sum_{i \in L_j} R_{U_i} \varepsilon_i - P_\lambda m_0 - Rem^{(j)}.$$

Also recall  $m_0^* = m_0 - P_\lambda m_0$ . Taking average of the above equation for all j over s, we have

(D.1) 
$$\bar{m} - m_0^* = \frac{1}{N} \sum_{i=1}^N \varepsilon_i R_{U_i} + \frac{1}{s} \sum_{j=1}^s Rem^{(j)}$$

which decomposes into

(D.2) 
$$\bar{\boldsymbol{\beta}} - \boldsymbol{\beta}_0^* = \frac{1}{N} \sum_{i=1}^N L_{U_i} \varepsilon_i - \frac{1}{s} \sum_{j=1}^s Rem_{\boldsymbol{\beta}}^{(j)},$$

and

(D.3) 
$$\bar{f} - f_0^* = \frac{1}{N} \sum_{i=1}^N N_{U_i} \varepsilon_i - \frac{1}{s} \sum_{j=1}^s Rem_f^{(j)}.$$

Similar to proof in Section 7.2, we can show that the first term weakly converges to a normal distribution, and the remainder term is asymptotically ignorable. Recall the definition of  $m_0^* = (id - P_\lambda)f_0$ .

Therefore, we deduct that

$$(D.4) \quad (\boldsymbol{x}^{T}, 1) \left( \begin{array}{c} \sqrt{N}(\bar{\boldsymbol{\beta}} - \boldsymbol{\beta}_{0}^{*}) \\ \sqrt{Nh}(\bar{f}(z_{0}) - f_{0}^{*}(z_{0})) \end{array} \right) \\ = \sqrt{N} \boldsymbol{x}^{T}(\bar{\boldsymbol{\beta}} - \boldsymbol{\beta}_{0}^{*}) + (Nh)^{\frac{1}{2}}(\bar{f}(z_{0}) - f_{0}^{*}(z_{0})) \\ \leq \frac{1}{\sqrt{N}} \sum_{i=1}^{N} (\varepsilon_{i} \boldsymbol{x}^{T} L_{U_{i}} + h^{1/2} \varepsilon_{i} N_{U_{i}}) \\ \frac{1}{s} \sum_{j=1}^{s} \sqrt{N} \boldsymbol{x}^{T} Rem_{\beta}^{(j)} - \frac{1}{s} \sum_{j=1}^{s} \sqrt{Nh} Rem_{f}^{(j)}(z_{0}).$$

We can show that the first term is asymptotic normal by central limit theorem: first note that the summands are i.i.d. and with mean zero. Moreover, by Proposition 2.3,

$$\begin{aligned} \boldsymbol{x}^{T} L_{U} + h^{1/2} N_{U}(z_{0}) &= \boldsymbol{x}^{T} L_{U} + h^{1/2} (\widetilde{K}_{Z}(z_{0}) - \boldsymbol{A}(z_{0})^{T} L_{U}) \\ &= (\boldsymbol{x} - h^{1/2} \boldsymbol{A}(z_{0}))^{T} L_{U} + h^{1/2} \widetilde{K}_{Z}(z_{0}) \end{aligned}$$

We compute

$$\mathbb{E}\left[(\boldsymbol{x}^{T}L_{U_{i}} + h^{1/2}N_{U_{i}}(z_{0}))^{2}\right]$$
(D.5)
$$=\underbrace{\mathbb{E}\left[(\boldsymbol{x} - h^{1/2}\boldsymbol{A}(z_{0}))^{T}L_{U}L_{U}^{T}(\boldsymbol{x} - h^{1/2}\boldsymbol{A}(z_{0}))\right]}_{(I)}$$

$$+\underbrace{\mathbb{E}\left[h\widetilde{K}_{Z}(z_{0})^{2}\right]}_{(II)} +\underbrace{\mathbb{E}\left[2h^{1/2}\widetilde{K}_{Z}(z_{0})(\boldsymbol{x} - h^{1/2}\boldsymbol{A}(z_{0}))^{T}L_{U}\right]}_{(III)}$$

For the second term in (D.5), we have

(D.6) 
$$(II) = \mathbb{E}[h\widetilde{K}_Z(z_0)^2] = h \|\widetilde{K}_{z_0}\|_{L_2(\mathbb{P}_Z)}^2 \to \sigma_{z_0}^2.$$

For the first term in (D.5), recall from Section 7.2 that  $\mathbb{E}[L_U L_U^T] \to \Omega^{-1}$ ,  $h^{1/2} \mathbf{A}(z_0) \to -\gamma_{z_0}$ . Hence we have

(D.7) 
$$(I) \to (\boldsymbol{x} + \gamma_{z_0})^T \Omega^{-1} (\boldsymbol{x} + \gamma_{z_0}).$$

Moreover, recall from Section 7.2 that

$$h^{1/2}\mathbb{E}\big[\widetilde{K}_Z(z_0)L_U\big] \to \Omega^{-1}\alpha_{z_0}.$$

Therefore it follows that

(D.8) 
$$(III) \rightarrow 2(\boldsymbol{x} + \gamma_{z_0})^T \Omega^{-1} \alpha_{z_0}.$$

Hence combining (D.7), (D.6) and (D.8), the limit of (D.5) is

$$\mathbb{E}\left[(\boldsymbol{x}^T L_{U_i} + h^{1/2} N_{U_i}(z_0))^2\right] \to \boldsymbol{x}^T \Omega^{-1} \boldsymbol{x} + 2\boldsymbol{x}^T \Sigma_{12} + \Sigma_{22},$$

for any  $\boldsymbol{x} \in \mathbb{R}^p$ . Therefore the limit distribution follows by central limit theorem. Now for the remainder terms, by Lemma 7.3, if Condition (3.6) is satisfied, we have

$$\begin{aligned} |\frac{1}{s} \sum_{j=1}^{s} \sqrt{N} \boldsymbol{x}^{T} Rem_{\beta}^{(j)}| &\leq C \sqrt{N} \|\frac{1}{s} \sum_{j=1}^{s} Rem_{\beta}^{(j)}\|_{2} \\ &= o_{P}(N^{1/2} s^{-1/2} b_{n,s} \log n). \end{aligned}$$

and

$$\begin{aligned} |\frac{1}{s} \sum_{j=1}^{s} \sqrt{Nh} \boldsymbol{x}^{T} Rem_{f}^{(j)}(z_{0})| &\leq C\sqrt{Nh} \|\frac{1}{s} \sum_{j=1}^{s} Rem_{f}^{(j)}\|_{\sup} \\ &\leq C' N^{1/2} \|\frac{1}{s} \sum_{j=1}^{s} Rem_{f}^{(j)}\|_{\mathcal{C}} \\ &= o_{P}(N^{1/2} s^{-1/2} b_{n,s} \log n). \end{aligned}$$

where in the second inequality we used Lemma A.1. Then if Condition (3.7)

is satisfied, we have  $N^{1/2}s^{-1/2}b_{n,s}\log n \to 0$ . Hence by (D.4), it follows that

$$(\boldsymbol{x}^{T}, 1) \left( \begin{array}{c} \sqrt{N}(\bar{\boldsymbol{\beta}} - \boldsymbol{\beta}_{0}^{*}) \\ \sqrt{Nh}(\bar{f}(z_{0}) - f_{0}^{*}(z_{0})) \end{array} \right) \to N (0, \sigma^{2}(\boldsymbol{x}^{T}\Omega^{-1}\boldsymbol{x} + 2\boldsymbol{x}^{T}\Sigma_{12} + \Sigma_{22})).$$

Hence the conclusion follows by the arbitrariness of x using Wold device.  $\Box$ 

## APPENDIX E: PROOFS OF LEMMAS IN SECTION 7

### E.1. Proof of Lemma 7.1.

PROOF. Recall from Section 7.3 that

$$Z_n(\widetilde{m}) = \frac{1}{2}h^{1/2}n^{1/2}d_{n,s}^{-1}Rem^{(j)} = \frac{1}{2}c_r^{-1}hn^{1/2}r_{n,s}^{-1}Rem^{(j)}$$

We showed in Section 7.3 that  $Z_n(m)$  is a sub-Gaussian process. Letting  $\mathbb{U}^{(j)} = (\mathbb{X}^{(j)}, \mathbb{Z}^{(j)})$ , where  $\mathbb{X}^{(j)}$  and  $\mathbb{Z}^{(j)}$  are designs on *j*-th sub-population. Without causing any confusion, we can remove the the superscript (j). We have

$$\mathbb{E}[\|Rem^{(j)}\|_{\mathcal{A}}^{2}] = \mathbb{E}\left[\mathbb{E}[\|Rem^{(j)}\|_{\mathcal{A}}^{2} | \mathbb{U}]\right]$$
  
(E.1) 
$$= \mathbb{E}\left[\mathbb{E}[\|Rem^{(j)}\|_{\mathcal{A}}^{2} | \mathbb{U}]I_{\mathcal{E}}\right] + \mathbb{E}\left[\mathbb{E}[\|Rem^{(j)}\|_{\mathcal{A}}^{2} | \mathbb{U}]I_{\mathcal{E}^{c}}\right],$$

where  ${\mathcal E}$  is the event defined in Section 7.3. For the first term in (E.1), we have

$$\begin{split} \mathbb{E} \Big[ \mathbb{E} [\|Rem^{(j)}\|_{\mathcal{A}}^{2} |\mathbb{U}] I_{\mathcal{E}} \Big] \\ &= 4c_{r}^{2}h^{-2}n^{-1}r_{n,s}^{2}\mathbb{E} \Big[ \mathbb{E} [\|Z_{n}(\widetilde{m})\|_{\mathcal{A}}^{2} |\mathbb{U}] I_{\mathcal{E}} \Big] \\ &= 4c_{r}^{2}h^{-2}n^{-1}r_{n,s}^{2} \int_{0}^{\infty} \mathbb{P} \Big( \mathbb{E} [\|Z_{n}(\widetilde{m})\|_{\mathcal{A}}^{2} |\mathbb{U}] I_{\mathcal{E}} \ge x \Big) dx \\ &= 4c_{r}^{2}h^{-2}n^{-1}r_{n,s}^{2} \Big\{ \int_{0}^{\omega(\mathcal{F},1)^{2}} \mathbb{P} \Big( \mathbb{E} [\|Z_{n}(\widetilde{m})\|_{\mathcal{A}}^{2} |\mathbb{U}] I_{\mathcal{E}} \ge x \Big) dx \\ &+ \int_{\omega(\mathcal{F},1)^{2}}^{\infty} \mathbb{P} \Big( \mathbb{E} [\|Z_{n}(\widetilde{m})\|_{\mathcal{A}}^{2} |\mathbb{U}] I_{\mathcal{E}} \ge x \Big) dx \Big\} \\ &\leq 4c_{r}^{2}h^{-2}n^{-1}r_{n,s}^{2} \Big\{ \omega(\mathcal{F},1)^{2} + \int_{0}^{\infty} \mathbb{P} \big( \mathbb{E} [\|Z_{n}(\widetilde{m})\|_{\mathcal{A}}^{2} |\mathbb{U}] I_{\mathcal{E}} \ge x + \omega(\mathcal{F},1)^{2} \big) dx \Big\} \end{split}$$

In Section 7.3 we proved that  $\mathcal{E} \subset \{ \widetilde{m} \in \mathcal{F} \}$ . Therefore we have

$$\mathbb{E}[\|Z_n(\widetilde{m})\|_{\mathcal{A}}^2 \,|\, \mathbb{U}]I_{\mathcal{E}} \le \sup_{m \in \mathcal{F}} \|Z_n(m)\|_{\mathcal{A}}^2.$$

and by Lemma F.1 and the fact that diam $(\mathcal{F}) \leq 1$ , we have  $\mathbb{P}\Big(\sup_{m \in \mathcal{F}} \|Z_n(m)\|_{\mathcal{A}}^2 \geq x + \omega(\mathcal{F}, 1)^2\Big) \leq \mathbb{P}\Big(\sup_{m \in \mathcal{F}} \|Z_n(m)\|_{\mathcal{A}} \geq (\sqrt{x} + \omega(\mathcal{F}, 1))/2\Big)$   $\leq C \exp(-x/C).$  Hence it follows that

$$\mathbb{E} \big[ \mathbb{E} [ \| \operatorname{Rem}^{(j)} \|_{\mathcal{A}}^{2} | \mathbb{U}] I_{\mathcal{E}} \big] \leq 2c_{r}^{2} h^{-2} n^{-1} r_{n,s}^{2} \Big( \omega(\mathcal{F}, 1)^{2} + \int_{0}^{\infty} C \exp(-x/C) dx \Big)$$

$$(E.2) \qquad = 2c_{r}^{2} h^{-2} n^{-1} r_{n,s}^{2} \big( \omega(\mathcal{F}, 1)^{2} + C^{2} \big).$$

We now turn to control the second term in (E.1). By Lemma G.2, we get that  $\mathbb{E}[\|\Delta f^{(j)}\|_{\mathcal{H}}^2 |\mathbb{U}] \leq 2\sigma^2/\lambda + 4\|f_0\|_{\mathcal{H}}^2$ . Also by first order optimality condition with respect to  $\hat{\beta}$ ,

$$\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_0^{(j)} = (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T (f_0(\mathbb{Z}) - \widehat{f}^{(j)}(\mathbb{Z}) + \boldsymbol{\varepsilon}^{(j)}),$$

where we omitted the superscript of (j) for the designs  $\mathbb{X}^{(j)}$  and  $\mathbb{Z}^{(j)}$ . Hence

$$\|\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}\|_{2}^{2} \leq 2\|(\mathbb{X}^{T}\mathbb{X})^{-1}\mathbb{X}^{T}\boldsymbol{\varepsilon}^{(j)}\|_{2}^{2} + 2\|(\mathbb{X}^{T}\mathbb{X})^{-1}\mathbb{X}^{T}(f_{0}(\mathbb{Z}) - \widehat{f}^{(j)}(\mathbb{Z}))\|_{2}^{2},$$

Taking conditional expectation yields

(E.3) 
$$\mathbb{E}[\|\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_{0}^{(j)}\|_{2}^{2} | \mathbb{U}] \leq 2\mathbb{E}[\|(\mathbb{X}^{T}\mathbb{X})^{-1}\mathbb{X}^{T}\boldsymbol{\varepsilon}^{(j)}\|_{2}^{2} | \mathbb{U}] + 2\mathbb{E}[\|(\mathbb{X}^{T}\mathbb{X})^{-1}\mathbb{X}^{T}(f_{0}(\mathbb{Z}) - \widehat{f}^{(j)}(\mathbb{Z}))\|_{2}^{2} | \mathbb{U}].$$

Denote  $\widehat{\Sigma}^{(j)} = \mathbb{X}^T \mathbb{X}$ , we first control the first term (E.3). Note that

$$(\mathbb{X}^T\mathbb{X})^{-1}\mathbb{X}^T\boldsymbol{\varepsilon}^{(j)} = \frac{1}{n}\sum_{i\in L_j} (\widehat{\Sigma}^{(j)})^{-1}\boldsymbol{X}_i\varepsilon_i.$$

Taking conditional expectation and by independence, we have

$$\mathbb{E}\left[\|(\mathbb{X}^T\mathbb{X})^{-1}\mathbb{X}^T\boldsymbol{\varepsilon}^{(j)}\|_2^2 \,|\,\mathbb{U}\right] = \mathbb{E}\left[\|\frac{1}{n}\sum_{i\in L_j}(\widehat{\Sigma}^{(j)})^{-1}\boldsymbol{X}_i\varepsilon_i\|_2^2 \,|\,\mathbb{U}\right]$$
$$= \frac{1}{n^2}\sum_{i\in L_j}\mathbb{E}\left[(\widehat{\Sigma}^{(j)})^{-1}\boldsymbol{X}_i\varepsilon_i\|_2^2 \,|\,\mathbb{U}\right]$$
$$= \frac{1}{n^2}\sum_{i\in L_j}\sigma^2\|(\widehat{\Sigma}^{(j)})^{-1}\boldsymbol{X}_i\|_2^2.$$
(E.4)

For the second term in (E.3), we have similar to above that

$$(\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T (f_0(\mathbb{Z}) - \widehat{f}^{(j)}(\mathbb{Z})) = \frac{1}{n} \sum_{i \in L_j} (\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i (f_0(Z_i) - \widehat{f}^{(j)}(Z_i)).$$

Taking conditional expectation, we have

$$\mathbb{E} \left[ \| (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T (f_0(\mathbb{Z}) - \widehat{f}^{(j)}(\mathbb{Z})) \|_2^2 | \mathbb{U} \right] \\ = \mathbb{E} \left[ \| \frac{1}{n} \sum_{i \in L_j} (\widehat{\Sigma}^{(j)})^{-1} \mathbf{X}_i (f_0(Z_i) - \widehat{f}^{(j)}(Z_i)) \|_2^2 | \mathbb{U} \right] \\ \le \frac{1}{n} \sum_{i \in L_j} \mathbb{E} \left[ \| (\widehat{\Sigma}^{(j)})^{-1} \mathbf{X}_i (f_0(Z_i) - \widehat{f}^{(j)}(Z_i)) \|_2^2 | \mathbb{U} \right]$$

where the inequality is by  $(\sum_{i=1}^{n} a_i)^2 \le n \sum_{i=1}^{n} a_i^2$ . Hence we have

$$\mathbb{E}\left[\|(\mathbb{X}^{I} \mathbb{X})^{-1} \mathbb{X}^{I} (f_{0}(\mathbb{Z}) - f^{(j)}(\mathbb{Z}))\|_{2}^{2} |\mathbb{U}\right] \\
\leq \frac{1}{n} \sum_{i \in L_{j}} \mathbb{E}\left[(f_{0}(Z_{i}) - \widehat{f}^{(j)}(Z_{i}))^{2} |\mathbb{U}\right] \|(\widehat{\Sigma}^{(j)})^{-1} \mathbf{X}_{i}\|_{2}^{2} \\
\leq \frac{1}{n} \sum_{i \in L_{j}} \mathbb{E}\left[\|f_{0} - \widehat{f}^{(j)}\|_{\sup}^{2} |\mathbb{U}\right] \|(\widehat{\Sigma}^{(j)})^{-1} \mathbf{X}_{i}\|_{2}^{2} \\
\leq \frac{1}{n} \sum_{i \in L_{j}} c_{k} \mathbb{E}\left[\|f_{0} - \widehat{f}^{(j)}\|_{\mathcal{H}}^{2} |\mathbb{U}\right] \|(\widehat{\Sigma}^{(j)})^{-1} \mathbf{X}_{i}\|_{2}^{2} \\
\leq \frac{1}{n} \sum_{i \in L_{j}} c_{k} (2\sigma^{2}/\lambda + 4\|f_{0}\|_{\mathcal{H}}^{2}) \|(\widehat{\Sigma}^{(j)})^{-1} \mathbf{X}_{i}\|_{2}^{2},$$
(E.5)

where  $c_k = \sup_z K(z, z)$ . The second last inequality follows from the fact that  $||f||_{\sup} \leq \sup_z ||K_z||_{\mathcal{H}} ||f||_{\mathcal{H}} = c_k^{1/2} ||f||_{\mathcal{H}}$  and the last inequality is by Lemma G.2. Combing (E.4) and (E.5), we have by (E.3) that

$$\mathbb{E}[\|\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_{0}^{(j)}\|_{2}^{2} |\mathbb{U}] \leq C\lambda^{-1} \frac{1}{n} \sum_{i \in L_{j}} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_{i}\|_{2}^{2}$$

holds almost surely for some constant C As we have  $\|\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_0^{(j)}\|_{L_2(\mathbb{P}_X)}^2 = (\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_0^{(j)})^T \Sigma(\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_0^{(j)}) \leq \|\Sigma^{-1/2}\| \|\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_0^{(j)}\|_2^2,$ it follows that

(E.6) 
$$\mathbb{E}[\|\widehat{\boldsymbol{\beta}}^{(j)} - \boldsymbol{\beta}_{0}^{(j)}\|_{L_{2}(\mathbb{P}_{X})}^{2} | \mathbb{U}] \leq C\lambda^{-1} \frac{1}{n} \sum_{i \in L_{j}} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_{i}\|_{2}^{2},$$

for a constant C that is different from above. Lastly, we have  $\|\widehat{f}^{(j)} - f_0\|_{L_2(\mathbb{P}_Z)} \leq \|\widehat{f}^{(j)} - f_0\|_{\sup} \leq c_k^{1/2} \|\widehat{f}^{(j)} - f_0\|_{\mathcal{H}}$ , and it follows that (E.7)  $\mathbb{E}[\|\widehat{f}^{(j)} - f_0\|_{L_2(\mathbb{P}_Z)}^2 |\mathbb{U}] \lesssim \lambda^{-1}.$ 

Note that for any  $m = (\boldsymbol{\beta}, f), \ \|m\|_{\mathcal{A}}^2 = \|\boldsymbol{X}^T \boldsymbol{\beta} + f(Z)\|_{L_2(\mathbb{P}_U)}^2 + \lambda \|f\|_{\mathcal{H}}^2 \leq 1$ 

$$2\|\boldsymbol{\beta}\|_{L_{2}(\mathbb{P}_{X})}^{2} + 2\|f\|_{L_{2}(\mathbb{P}_{Z})}^{2} + \lambda\|f\|_{\mathcal{H}}^{2}. \text{ Hence by (E.6), (E.7) and (G.1), we have}$$
$$\mathbb{E}\left[\|\Delta m^{(j)}\|_{\mathcal{A}}^{2} \,|\,\mathbb{U}\right] \leq C\lambda^{-1}n^{-1}\sum_{i\in L_{j}}\|(\widehat{\Sigma}^{(j)})^{-1}\boldsymbol{X}_{i}\|_{2}^{2}.$$

Moreover,

$$\|Rem^{(j)}\|_{\mathcal{A}} \leq \|\frac{1}{n} \sum_{i \in L_j} \Delta m^{(j)}(U_i) R_{U_i}\|_{\mathcal{A}} + \|\mathbb{E}_U[\Delta m^{(j)}(U) R_U]\|$$
  
$$= \frac{1}{n} \sum_{i \in L_j} \|\Delta m^{(j)}(U_i) R_{U_i}\|_{\mathcal{A}} + \mathbb{E}_U[\|\Delta m^{(j)}(U) R_U\|]$$
  
$$\leq 2h^{-1} \|\Delta m^{(j)}\|_{\mathcal{A}},$$

where in the last inequality we used  $|\Delta m^{(j)}(U)| \leq h^{-1/2} ||\Delta m^{(j)}||_{\mathcal{A}}$  and  $||R_U||_{\mathcal{A}} \leq h^{-1/2}$ . Hence

$$\mathbb{E} \left[ \|Rem^{(j)}\|_{\mathcal{A}}^2 \,|\, \mathbb{U} \right] \le 4h^{-2} \mathbb{E} \left[ \|\Delta m^{(j)}\|_{\mathcal{A}}^2 \,|\, \mathbb{U} \right] \le Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} \sum_{i \in L_j} \|(\widehat{\Sigma}^{(j)})^{-1} \boldsymbol{X}_i\|_2^2 + Ch^{-2} \lambda^{-1} n^{-1} n^{-1}$$

Hence, we have that the second term in (E.1)

$$\mathbb{E}\left[\mathbb{E}\left[\|\operatorname{Rem}^{(j)}\|_{\mathcal{A}}^{2} | \mathbb{U}\right] I_{\mathcal{E}^{c}}\right] \leq Ch^{-2}\lambda^{-1}n^{-1}\sum_{i\in L_{j}}\mathbb{E}\left[\|(\widehat{\Sigma}^{(j)})^{-1}\boldsymbol{X}_{i}\|_{2}^{2}I_{\mathcal{E}^{c}}\right]$$
$$\leq Ch^{-2}\lambda^{-1}n^{-1}\mathbb{P}(\mathcal{E}^{c})\sum_{i\in L_{j}}\mathbb{E}\left[\|(\widehat{\Sigma}^{(j)})^{-1}\boldsymbol{X}_{i}\|_{2}^{4}\right]$$
$$(E.8) \leq C'h^{-2}\lambda^{-1}\mathbb{P}(\mathcal{E}^{c}),$$

where the second last inequality is by Holder's inequality and the last one by assumption on the design. By (E.8) and Lemma 7.4, we obtain

(E.9) 
$$\mathbb{E}\left[\mathbb{E}\left[\|Rem^{(j)}\|_{\mathcal{A}}^{2} |\mathbb{U}]I_{\mathcal{E}^{c}}\right] \lesssim h^{-2}\lambda^{-1}n\exp(-c\log^{2}N)\right]$$

Finally, plugging (E.2) and (E.9) into (E.1), we have for sufficiently large n, (E.10)

$$\mathbb{E}[\|Rem^{(j)}\|_{\mathcal{A}}^{2}] \leq 2c_{r}^{2}h^{-2}n^{-1}r_{n,s}^{2}(\omega(\mathcal{F},1)^{2}+C) + C'h^{-2}\lambda^{-1}n\exp(-c\log^{2}N),$$
as desired.

We can apply similar arguments as above to bound  $\|Rem_f^{(j)}\|_{\mathcal{C}}$  and  $\|1/s\sum_{j=1}^s Rem_f^{(j)}\|_{\mathcal{C}}$ , by changing  $\omega(\mathcal{F}, 1)$  to  $\omega(\mathcal{F}_2, 1)$ , which is dominated by  $\omega(\mathcal{F}, 1)$ . The bounds of  $\|Rem_{\beta}^{(j)}\|_2$  and  $\|1/s\sum_{j=1}^s Rem_{\beta}^{(j)}\|_2$  then follow from triangular inequality.

## E.2. Proof of Lemma 7.2.

**PROOF.** The main term (I) can be rearranged as follows:

$$(I) = \underbrace{\frac{1}{\sqrt{n}} \sum_{i \in L_j} \varepsilon_i \left( \boldsymbol{x}^T L_{U_i} + s^{-1/2} h^{1/2} N_{U_i}(z_0) \right)}_{(III)} + \underbrace{\frac{1}{\sqrt{N}} \sum_{i \notin L_j} h^{1/2} N_{U_i}(z_0) \varepsilon_i}_{(IV)}}_{(IV)}$$

When analyzing (I), we consider two cases: (1)  $s \to \infty$  and (2) s is fixed.

Case 1:  $s \to \infty$ . We first apply CLT to the first component of term (III), i.e.,  $\frac{1}{\sqrt{n}} \sum_{i \in L_j} \varepsilon_i \boldsymbol{x}^T L_{U_i}$ . The summands are i.i.d. with mean zero. Moreover,

$$\mathbb{E}\big[(\varepsilon \boldsymbol{x}^T L_U)^2\big] = \sigma^2 \boldsymbol{x}^T \mathbb{E}[L_U L_U^T] \boldsymbol{x}$$

By Proposition 2.3,

$$\mathbb{E}[L_U L_U^T] = (\Omega + \Sigma_\lambda)^{-1} \mathbb{E}[(\boldsymbol{X} - \boldsymbol{A}(Z))(\boldsymbol{X} - \boldsymbol{A}(Z))^T](\Omega + \Sigma_\lambda)^{-1}$$

By Lemma A.3 in Section A.1, we have that  $\Sigma_{\lambda} = \mathbb{E}_{Z} [\boldsymbol{B}(Z) (\boldsymbol{B}(Z) - \boldsymbol{A}(Z))^{T}] \rightarrow 0$ , and also

$$\mathbb{E}[(\boldsymbol{X} - \boldsymbol{A}(Z))(\boldsymbol{X} - \boldsymbol{A}(Z))^{T}]$$
  
=  $\mathbb{E}[(\boldsymbol{X} - \boldsymbol{B}(Z))(\boldsymbol{X} - \boldsymbol{B}(Z))^{T}] + \mathbb{E}[(\boldsymbol{B}(Z) - \boldsymbol{A}(Z))(\boldsymbol{B}(Z) - \boldsymbol{A}(Z))^{T}]$   
+ $2\mathbb{E}[(\boldsymbol{X} - \boldsymbol{A}(Z))(\boldsymbol{B}(Z) - \boldsymbol{A}(Z))^{T}] \rightarrow \Omega^{-1}$ 

This implies  $\mathbb{E}[L_U L_U^T] \to \Omega^{-1}$ . Therefore by CLT, we have

(E.11) 
$$\frac{1}{\sqrt{n}} \sum_{i \in L_j} \varepsilon_i \boldsymbol{x}^T L_{U_i} \rightsquigarrow N(0, \sigma^2 \boldsymbol{x}^T \Omega^{-1} \boldsymbol{x}).$$

We next consider  $\frac{1}{\sqrt{n}} \sum_{i \in L_j} s^{-1/2} h^{1/2} N_{U_i}(z_0) \varepsilon_i$  which is the second component in (III). Again the summands are i.i.d. with mean zero. By Proposition 2.3 we have

$$(E.12) \qquad \mathbb{E}\left[ (h^{1/2} \varepsilon N_U(z_0))^2 \right] \\ = \sigma^2 h \mathbb{E}\left[ (\widetilde{K}_Z(z_0) - L_U^T \boldsymbol{A}(z_0))^2 \right] \\ = \sigma^2 h \mathbb{E}\left[ \widetilde{K}_Z(z_0)^2 \right] + \sigma^2 h \boldsymbol{A}(z_0)^T \mathbb{E}[L_U L_U^T] \boldsymbol{A}(z_0) \\ -2\sigma^2 h \mathbb{E}[\widetilde{K}_Z(z_0) L_U^T \boldsymbol{A}(z_0)] \right]$$

For the first term in (E.12), by condition in the lemma, we have

$$\sigma^2 h \mathbb{E} \left[ \widetilde{K}_Z(z_0)^2 \right] = h \| \widetilde{K}_{z_0} \|_{L_2(\mathbb{P}_Z)}^2 \to \sigma^2 \sigma_{z_0}^2$$

For the second term in (E.12), as  $h^{1/2} \mathbf{A}(z_0) \to -\gamma_{z_0}$ , and  $\mathbb{E}[L_U L_U^T] \to \Omega^{-1}$ , we have

$$\sigma^2 h \boldsymbol{A}(z_0)^T \mathbb{E}[L_U L_U^T] \boldsymbol{A}(z_0) \to \sigma^2 \gamma_{z_0}^T \Omega^{-1} \gamma_{z_0}.$$

For the last term in (E.12), we consider

$$h^{1/2}\mathbb{E}\big[\widetilde{K}_Z(z_0)L_U\big] = h^{1/2}(\Omega + \Sigma_\lambda)^{-1}\mathbb{E}[\widetilde{K}_Z(z_0)(\boldsymbol{X} - \boldsymbol{A}(Z))].$$
  
We have  $(\Omega + \Sigma_\lambda)^{-1} \to \Omega^{-1}$  and

$$\mathbb{E}[\widetilde{K}_{Z}(z_{0})(\boldsymbol{X}-\boldsymbol{A}(Z))] = h^{1/2}(\langle \boldsymbol{B}, \widetilde{K}_{z_{0}} \rangle_{L_{2}(\mathbb{P}_{Z})} - \langle \boldsymbol{A}, \widetilde{K}_{z_{0}} \rangle_{L_{2}(\mathbb{P}_{Z})})$$

$$= h^{1/2}(\langle \boldsymbol{A}, \widetilde{K}_{z_{0}} \rangle_{\mathcal{C}} - \langle \boldsymbol{A}, \widetilde{K}_{z_{0}} \rangle_{L_{2}(\mathbb{P}_{Z})})$$

$$= h^{1/2}\lambda\langle \boldsymbol{A}, \widetilde{K}_{z_{0}} \rangle_{\mathcal{H}}$$

$$= h^{1/2}\langle W_{\lambda}\boldsymbol{A}, \widetilde{K}_{z_{0}} \rangle_{\mathcal{C}}$$

$$= h^{1/2}W_{\lambda}\boldsymbol{A}(z_{0}) \rightarrow \alpha_{z_{0}}$$

Hence  $h^{1/2}\mathbb{E}\big[\widetilde{K}_Z(z_0)L_U\big] \to \Omega^{-1}\alpha_{z_0}$  and so  $h\mathbb{E}[\widetilde{K}_Z(z_0)L_U^T \mathbf{A}(z_0)] \to \gamma_{z_0}^T \Omega^{-1}\alpha_{z_0}$ . In summary, we have

$$\mathbb{E}\left[(h^{1/2}\varepsilon N_U(z_0))^2\right] \to \sigma^2 \left(\sigma_{z_0}^2 + \gamma_{z_0}^T \Omega^{-1} \gamma_{z_0} + 2\gamma_{z_0}^T \Omega^{-1} \alpha_{z_0}\right) = \Sigma_{22}.$$

By central limit theorem, it follows that

(E.13) 
$$\frac{1}{\sqrt{n}} \sum_{i \in L_j} \varepsilon_i h^{1/2} N_{U_i}(z_0) \rightsquigarrow N(0, \sigma^2 \Sigma_{22}).$$

As  $s \to \infty$ , we have  $\frac{1}{\sqrt{n}} \sum_{i=1}^{n} \varepsilon_i s^{-1/2} h^{1/2} N_{U_i}(z_0) \to 0$ . So the second component in (III) is asymptotically ignorable. Therefore by (E.11), we obtain

 $(III) \rightsquigarrow N\left(0, \sigma^2 \boldsymbol{x}^T \Omega^{-1} \boldsymbol{x}\right).$ 

As for (IV), we apply similar arguments as in the previous paragraph and consider  $s \to \infty$ . It follows that

$$(IV) = \sqrt{1 - s^{-1}} \Big\{ \frac{1}{\sqrt{N - n}} \sum_{i \notin L_j} h^{1/2} N_{U_i}(z_0) \varepsilon_i \Big\} \rightsquigarrow N(0, \sigma^2 \Sigma_{22}).$$

Lastly, note that (III) and (IV) are independent, so are their limits. Therefore, it follows that

 $(I) \rightsquigarrow N(0, \sigma^2(\boldsymbol{x}^T \Omega^{-1} \boldsymbol{x} + \Sigma_{22})).$ 

Case 2: s fixed. Instead of decomposing (III) into two components as in previous case, we apply CLT to term (III) as a whole. Note that the summands in (III) are i.i.d. with mean zero. Moreover,

$$\mathbb{E} \Big[ \varepsilon^2 \big( \boldsymbol{x}^T L_U + s^{-1/2} h^{1/2} N_U(z_0) \big)^2 \Big] \\ = \sigma^2 \mathbb{E} \big[ (\boldsymbol{x}^T L_U)^2 \big] + s^{-1} \sigma^2 \mathbb{E} \big[ (h^{1/2} N_U(z_0))^2 \big] \\ + 2s^{-1/2} \sigma^2 \mathbb{E} \big[ h^{1/2} \boldsymbol{x}^T L_U N_U(z_0) \big] \Big]$$

The first two terms are considered in Case 1. For the third term, we have

$$\mathbb{E}\left[\boldsymbol{x}^{T}L_{U}h^{1/2}N_{U}(z_{0})\right] = \mathbb{E}\left[h^{1/2}\boldsymbol{x}^{T}L_{U}\left(\widetilde{K}_{Z}(z_{0}) - L_{U}^{T}\boldsymbol{A}(z_{0})\right)\right]$$

From Case 1, we have  $h^{1/2}\mathbb{E}[\widetilde{K}_Z(z_0)L_U] \to \alpha_{z_0}$ ,  $\mathbb{E}[L_UL_U^T] \to \Omega^{-1}$ , and  $h^{1/2}A(z_0) \to -\gamma_{z_0}$ . It follows that

(E.14) 
$$\mathbb{E}[h^{1/2}\boldsymbol{x}^T L_U N_U(z_0)] \to \boldsymbol{x}^T \Omega^{-1}(\alpha_{z_0} + \gamma_{z_0})$$

Therefore, we have

$$\mathbb{E}\Big[\varepsilon^2 \big( \boldsymbol{x}^T L_U + s^{-1/2} h^{1/2} N_U(z_0) \big)^2 \Big] \to \sigma^2 \big( \boldsymbol{x}^T \Omega^{-1} \boldsymbol{x} + s^{-1} \Sigma_{22} + 2s^{-1/2} \boldsymbol{x}^T \Sigma_{12} \big).$$

Hence by central limit theorem, we have

(III) 
$$\rightsquigarrow N(0, \sigma^2 (\boldsymbol{x}^T \Omega^{-1} \boldsymbol{x} + s^{-1} \Sigma_{22} + 2s^{-1/2} \boldsymbol{x}^T \Sigma_{12})).$$

Similarly, we have

$$(IV) \rightsquigarrow N(0, (1-s^{-1})\sigma^2 \Sigma_{22}).$$

As (III) and (IV) are independent, so are their limits. Therefore in the case that s is fixed, we have

$$(I) \rightsquigarrow N(0, \sigma^2 (\boldsymbol{x}^T \Omega^{-1} \boldsymbol{x} + \Sigma_{22} + 2s^{-1/2} \boldsymbol{x}^T \Sigma_{12})).$$

This finishes the proof.

#### E.3. Proof of Lemma 7.4.

PROOF. Recall that  $\Delta m^{(j)} = \hat{m}^{(j)} - m_0^{(j)}$ . As  $\Delta m^{(j)}$  minimizes the objective function (3.2), we have

$$\frac{1}{n} \sum_{i \in L_j} (\widehat{m}^{(j)}(U_i) - Y_i)^2 + \lambda \|\widehat{f}\|_{\mathcal{H}}^2 \le \frac{1}{n} \sum_{i \in L_j} (m_0(U_i) - Y_i)^2 + \lambda \|f_0\|_{\mathcal{H}}^2,$$

On the *j*-th sub-population, we have  $Y_i = m_0^{(j)}(U_i) + \varepsilon_i$ , hence it follows that

$$\frac{1}{n} \sum_{i \in L_j} (\widehat{m}^{(j)}(U_i) - m_0^{(j)}(U_i))^2 + \frac{2}{n} \sum_{i \in L_j} \varepsilon_i (\widehat{m}^{(j)}(U_i) - m_0^{(j)}(U_i)) + \lambda \|\widehat{f}^{(j)}\|_{\mathcal{H}}^2 \le \lambda \|f_0\|_{\mathcal{H}}^2.$$

Adding and subtracting  $\mathbb{E}_U[\Delta m^{(j)}(U)^2]$ , we transform the above inequality to

$$\frac{1}{n} \sum_{i \in L_j} \Delta m^{(j)}(U_i)^2 - \mathbb{E}_U[\Delta m^{(j)}(U)^2] + \mathbb{E}_U[\Delta m^{(j)}(U)^2] + \lambda \|\Delta f^{(j)}\|_{\mathcal{H}}^2$$
$$+ \frac{2}{n} \sum_{i \in L_j} \varepsilon_i \Delta m^{(j)}(U_i) - 2\lambda \|f_0\|_{\mathcal{H}}^2 + 2\lambda \langle \widehat{f}^{(j)}, f_0 \rangle_{\mathcal{H}} \le 0$$

As we have  $\mathbb{E}_{U}[\Delta m^{(j)}(U)^{2}] + \lambda \|\Delta f^{(j)}\|_{\mathcal{H}}^{2} = \|\Delta m^{(j)}\|_{L_{2}(\mathbb{P}_{U})}^{2} + \lambda \|\Delta f^{(j)}\|_{\mathcal{H}}^{2} =$ 

 $\|\Delta m^{(j)}\|_{\mathcal{A}}^2$ . It follows that

$$\|\Delta m^{(j)}\|_{\mathcal{A}}^{2} \leq -2\left(\frac{1}{n}\sum_{i\in L_{j}}\varepsilon_{i}\Delta m^{(j)}(U_{i}) - \lambda\langle\Delta f^{(j)}, f_{0}\rangle_{\mathcal{H}}\right)$$
$$-\frac{1}{n}\sum_{i\in L_{j}}\langle\Delta m^{(j)}(U_{i})R_{U_{i}} - \mathbb{E}_{U}[\Delta m^{(j)}(U)R_{U}], \Delta m^{(j)}\rangle_{\mathcal{A}}$$

(E.15) 
$$= -2\langle \frac{1}{n} \sum_{i \in L_j} \varepsilon_i R_{U_i} - P_{\lambda} m_0^{(j)}, \Delta m^{(j)} \rangle_{\mathcal{A}} - \langle Rem^{(j)}, \Delta m^{(j)} \rangle_{\mathcal{A}}.$$

Define the following two events:

$$\mathcal{B}_{1} := \left\{ \| \frac{1}{n} \sum_{i \in L_{j}} \varepsilon_{i} R_{U_{i}} \| \leq C \log^{2} N(nh)^{-1/2} \right\},\$$
$$\mathcal{B}_{2} := \left\{ \| Rem^{(j)} \|_{\mathcal{A}} \leq 2c_{r} h^{-1} n^{-1/2} (C\omega(1) + \log N) \| \Delta m^{(j)} \|_{\mathcal{A}} \right\}.$$

We bound the two terms in (E.15) respectively. First, note that

$$\begin{aligned} \|P_{\lambda}m_{0}^{(j)}\| &= \sup_{\|m\|_{\mathcal{A}}=1} |\langle P_{\lambda}m_{0}^{(j)}, m\rangle_{\mathcal{A}}| = \sup_{\|m\|_{\mathcal{A}}=1} \lambda |\langle f_{0}, f\rangle_{\mathcal{H}}| \\ &\leq \sup_{\|m\|=1} \sqrt{\lambda \|f_{0}\|_{\mathcal{H}}^{2}} \sqrt{\lambda \|f\|_{\mathcal{H}}^{2}} \leq \lambda^{1/2} \|f_{0}\|_{\mathcal{H}}, \end{aligned}$$

where the last inequality follows from the fact that  $\lambda \|f\|_{\mathcal{H}}^2 \leq \|m\|_{\mathcal{A}}^2 = 1$ . Therefore on event  $\mathcal{B}_1$ , the first term in (E.15) can be bounded by

$$\begin{aligned} \left| \langle \frac{1}{n} \sum_{i \in L_j} \varepsilon_i R_{U_i} - P_{\lambda} f_0, \Delta m^{(j)} \rangle_{\mathcal{A}} \right| &\leq \| \frac{1}{n} \sum_{i \in L_j} \varepsilon_i R_{U_i} - P_{\lambda} f_0 \|_{\mathcal{A}} \| \Delta m^{(j)} \|_{\mathcal{A}} \\ \end{aligned}$$

$$(E.16) &\leq C \left( \log^2 N(nh)^{-1/2} + \lambda^{1/2} \right) \| \Delta m^{(j)} \|_{\mathcal{A}} \end{aligned}$$

Furthermore, on the event  $\mathcal{B}_2$ , the second term in (E.15) can be bounded by

$$\begin{aligned} \left|\frac{1}{n}\sum_{i\in L_{j}}\langle Rem^{(j)},\Delta m^{(j)}\rangle_{\mathcal{A}}\right| &\leq \|\Delta m^{(j)}\|_{\mathcal{A}}\|Rem^{(j)}\|_{\mathcal{A}}\\ (E.17) &\leq 2c_{r}h^{-1}n^{-1/2}\big(C\omega(\mathcal{F},1)+\log N\big)\|\Delta m^{(j)}\|_{\mathcal{A}}^{2} \end{aligned}$$

Therefore, by (E.15), (E.16) and (E.17), it yields that on the event  $\mathcal{B}_1 \cap \mathcal{B}_2$  there exists a constant C,

$$\|\Delta m^{(j)}\|_{\mathcal{A}}^{2} \leq C'((nh)^{-1/2}\log^{2}N + \lambda^{1/2})\|\Delta m^{(j)}\|_{\mathcal{A}} + 2c_{r}h^{-1}n^{-1/2}(C\omega(\mathcal{F}, 1) + \log N)\|\Delta m^{(j)}\|_{\mathcal{A}}^{2}$$

If Condition (3.6) is satisfied, it implies that

$$h^{-1}n^{-1/2} (C\omega(1) + \log N) \le Cs^{1/2}N^{-1/2}h^{-1} (\omega(1) + \log N) = o(1).$$

Therefore it follows that

 $\|\Delta m^{(j)}\|_{\mathcal{A}} \le C_1((nh)^{-1/2}\log^2 N + \lambda^{1/2}) + o(1)\|\Delta m^{(j)}\|_{\mathcal{A}}$ 

which implies that for sufficiently large n,

$$\|\Delta m^{(j)}\|_{\mathcal{A}} \le C(\log^2 N(nh)^{-1/2} + \lambda^{1/2}).$$

Now we are left to bound the probability of  $\mathcal{B}_1^c \cup \mathcal{B}_2^c$ . For  $\mathcal{B}_1$ , define  $\mathcal{Q}_i = \{|\varepsilon_i| \leq \log N\}$ . Since  $||R_U|| \leq c_r h^{-1/2}$ , we have that on the event of  $\bigcap_{i \in L_j} \mathcal{Q}_i, \{\varepsilon_i R_{U_i}\}_{i \in L_j}$  is a sequence of random variables in Hilbert space  $\mathcal{A}$  that are independent with mean zero and bounded by  $ch^{-1/2} \log N$ . Therefore we have

$$\mathbb{P}(\mathcal{B}_{1}^{c}) = \mathbb{P}\left(\|\frac{1}{n}\sum_{i\in L_{j}}\varepsilon_{i}R_{U_{i}}\|_{\mathcal{A}} > C\log^{2}N(nh)^{-1/2}\right) \\
\leq \mathbb{P}\left(\bigcap_{i\in L_{j}}\mathcal{Q}_{i}, \|\frac{1}{n}\sum_{i\in L_{j}}\varepsilon_{i}R_{U_{i}}\|_{\mathcal{A}} > C\log^{2}N(nh)^{-1/2}\right) + \mathbb{P}\left(\left(\bigcap_{i}\mathcal{Q}_{i}\right)^{c}\right)$$

(E.18)  $\leq 2 \exp(-\log^2 N) + 2n \exp(-\log^2 N),$ 

where the first term in the last inequality is by Lemma G.1, and the second term is by union bound and the fact that  $\varepsilon_i$  are i.i.d. sub-Gaussian.

Now we turn to  $\mathcal{B}_2$ . Define  $\widetilde{m} := (2c_r)^{-1} h^{1/2} \frac{\Delta m^{(j)}}{\|\Delta m^{(j)}\|_{\mathcal{A}}}$ . Then it follows that

$$\|\widetilde{m}\|_{\sup} \le c_r h^{-1/2} \|\widetilde{m}\|_{\mathcal{A}} \le 1/2.$$

By the same argument as in Section 7.3, it follows that  $\|\Delta f^{(j)}\|_{\sup} \leq 1/2$ and  $|\boldsymbol{x}^T \Delta \boldsymbol{\beta}| \leq 1$  for all  $\boldsymbol{x}$ . Moreover, we have

$$\|\widetilde{f}\|_{\mathcal{H}} \le \lambda^{-1/2} \|\widetilde{m}\|_{\mathcal{A}} \le (2c_r)^{-1} h^{1/2} \lambda^{-1/2}$$

Hence we proved that  $\widetilde{m} \in \mathcal{F}$ . By Lemma F.1, it follows that

$$\mathbb{P}\Big(\|Z_n(\widetilde{m})\|_{\mathcal{A}} \ge C\omega(1, \operatorname{diam}(\mathcal{F})) + \log N\Big) \le C \exp\Big(-\log^2 N/C\Big).$$

By definition of  $Z_n(m)$  and  $\widetilde{m}$ , we have  $Z_n(\widetilde{m}) = (2c_r)^{-1}hn^{1/2} \|\Delta m^{(j)}\|_{\mathcal{A}}^{-1} Rem^{(j)}$ . Hence it follows that

$$\mathbb{P}(\mathcal{B}_2^c) = \mathbb{P}\Big(\|Rem^{(j)}\|_{\mathcal{A}} \ge 2c_r h^{-1} n^{-1/2} \big(C\omega(1) + \log N\big) \|\Delta m^{(j)}\|_{\mathcal{A}}\Big)$$
  
(E.19)  $\le C \exp\Big(-\log^2 n/C\Big).$ 

Combining (E.18) and (E.19), we have that for some universal constants c, C

and sufficiently large n,

$$\mathbb{P}\Big(\|\Delta m^{(j)}\|_{\mathcal{A}} \ge C\big((nh)^{-1/2}\log^2 N + \lambda^{1/2}\big)\Big) \le \mathbb{P}(\mathcal{B}_1^c) + \mathbb{P}(\mathcal{B}_2^c)$$
(E.20) 
$$\lesssim n\exp(-c\log^2 N).$$

This finishes the proof.

#### APPENDIX F: EMPIRICAL PROCESS LEMMA

**Lemma F.1** (Local chaining inequality). If  $Z_n(m) \in \mathcal{A}$  is a separable process on the metric space  $(\mathcal{F}, \|\cdot\|_{sup})$  and satisfies (7.15):

$$\mathbb{P}\Big(\|Z_n(m_1) - Z_n(m_2)\|_{\mathcal{A}} \ge t\Big) \le 2\exp\Big(-\frac{t^2}{8\|m_1 - m_2\|_{\sup}^2}\Big)$$

Then for all  $m_0 \in \mathcal{F}$  and  $x \ge 0$ , we have (F.1)  $\mathbb{P}\Big(\sup_{m \in \mathcal{F}} \|Z_n(m) - Z_n(m_0)\|_{\mathcal{A}} \ge C\omega(\mathcal{F}, \operatorname{diam}(\mathcal{F})) + x\Big) \le C \exp\left(-x^2/C\operatorname{diam}(\mathcal{F})^2\right),$ 

where C is a generic constant.

PROOF. The proof follows by modifying the proof of Theorem 5.28 in van Handel (2014). Let  $k_0$  be the largest integer such that  $2^{-k_0} \ge \text{diam}(\mathcal{F})$ . Then  $N(\mathcal{F}, d, 2^{-k}) = 1$  for all  $k \le k_0$ . We employ a chaining argument, and start at the scale  $2^{-k_0}$ . For every  $k > k_0$ , let  $N_k$  be a  $2^{-k}$  net such that  $|N_k| = N(T, d, 2^{-k})$ . We define the singleton  $N_{k_0} = \{m_0\}$ . We claim that

$$Z_n(m) = \lim_{k \to \infty} Z_n(\pi_k(m)) - Z_n(m_0)$$
  
=  $\sum_{k > k_0} \{ Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m)) \}$  a.s

where  $\pi_k(m)$  is the closes point in  $N_k$  to m. To prove this identity, note that the sub-Gaussian property of  $\{Z_n(m)\}_{m \in \mathcal{F}}$  implies that  $Z_n(m) - Z_n(\pi_k(m))$ is  $d(m, \pi_k(m))$ -sub-Gaussian. Thus

$$\sum_{k=k_0}^{\infty} \mathbb{E} \big[ \|Z_n(m) - Z_n(\pi_k(m))\|_{\mathcal{A}}^2 \big] \le \sum_{k=k_0}^{\infty} d(m, \pi_k(m))^2 \le \sum_{k=k_0}^{\infty} 2^{-k} < \infty.$$

It follows that  $||Z_n(m) - Z_n(\pi_k(m))||_{\mathcal{A}} \to 0$  a.s. as  $k \to \infty$ , and the chaining identity follows readily using the telescoping property of the sum. By the chaining identity and separability of  $\mathcal{F}$ , we obtain

$$\sup_{m \in \mathcal{F}} \|Z_n(m) - Z_n(m_0)\|_{\mathcal{A}} \le \sum_{k > k_0} \sup_{m \in \mathcal{F}} \|Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m))\|_{\mathcal{A}}.$$

By union bound and sub-Gaussian property, it follows that

$$\mathbb{P}\Big(\sup_{m\in\mathcal{F}} \|Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m))\|_{\mathcal{A}} > t\Big) \le 2|N_k| \exp\Big(-\frac{t^2}{8\cdot 2^{-2k}}\Big) \\ = 2\exp\Big(\log|N_k| - \frac{t^2}{8\cdot 2^{-2k}}\Big).$$

For large enough t, let  $u = \frac{t^2}{8 \cdot 2^{-2k}} - \log |N_k|$ , and we have  $\mathbb{P}\Big(\sup_{m \in \mathcal{F}} \|Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m))\|_{\mathcal{A}} > 2\sqrt{2} \cdot 2^{-k} (\sqrt{\log |N_k|} + u)\Big) \le 2 \exp^{u^2/2},$ 

which implies the link  $||Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m))||_{\mathcal{A}}$  at scale k is small. To show that the links at all scale of k are small simultaneously, we again use the union bound. Define the event  $\mathcal{D} := \{\exists k > k_0 \text{ s.t. } \sup_{m \in \mathcal{F}} ||Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m))||_{\mathcal{A}} > 2\sqrt{2} \cdot 2^{-k}(\sqrt{\log |N_k|} + u_k)\}$ , where  $u_k = x + \sqrt{k - k_0}$ . Then

$$\mathbb{P}(\mathcal{D}) \le \sum_{k>k_0} \mathbb{P}\Big(\sup_{m\in\mathcal{F}} \|Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m))\|_{\mathcal{A}} > 2\sqrt{2} \cdot 2^{-k}(\sqrt{\log|N_k|} + u_k)\Big) \le \sum_{k>k_0} \exp(-u_k^2/2) \le \exp(-x^2/2) \sum_{k>0} \exp(-k/2) \le C \exp(-x^2/2).$$

Moreover, by the fact that  $2^{-k_0} \leq 2 \operatorname{diam}(\mathcal{F})$  and

$$2^{-k_0} \le C 2^{-k_0 - 1} \sqrt{\log N(\mathcal{F}, d, 2^{-k_0 - 1})} \le C \sum_{k > k_0} \sqrt{\log |N_k|},$$

we have on the event  $\mathcal{D}^c$ ,

$$\begin{split} \sup_{m \in \mathcal{F}} \|Z_n(m) - Z_n(m_0)\|_{\mathcal{A}} \\ &\leq \sum_{k > k_0} \sup_{m \in \mathcal{F}} \|Z_n(\pi_k(m)) - Z_n(\pi_{k-1}(m))\|_{\mathcal{A}} \\ &\leq 2\sqrt{2} \sum_{k > k_0} 2^{-k} (\sqrt{\log |N_k|} + u_k) \\ &\leq 2\sqrt{2} \sum_{k > k_0} 2^{-k} \sqrt{\log |N_k|} + 2\sqrt{2} \cdot 2^{-k_0} \sum_{k > k_0} 2^{-k} \sqrt{k} + 2\sqrt{2} \sum_{k > k_0} 2^{-k} x \\ &\leq C \int_0^{\operatorname{diam}(\mathcal{F})} \sqrt{\log N(\mathcal{F}, d, \epsilon)} d\epsilon + C \operatorname{diam}(\mathcal{F}) x \\ &= C \omega(\mathcal{F}, \operatorname{diam}(\mathcal{F})) + C \operatorname{diam}(\mathcal{F}) x. \end{split}$$

Therefore

$$\mathbb{P}\Big(\sup_{m\in\mathcal{F}} \|Z_n(m) - Z_n(m_0)\|_{\mathcal{A}} \ge C\omega(\mathcal{F}, \operatorname{diam}(\mathcal{F})) + C\operatorname{diam}(\mathcal{F})x\Big)$$
$$\le \mathbb{P}(\mathcal{D}) \le C\exp(-x^2/2)$$

Replacing Cdiam $(\mathcal{F})x$  with a new variable x, we reach the conclusion of the lemma.

### APPENDIX G: AUXILIARY LEMMAS

**Lemma G.1.** (Pinelis, 1994) If  $\Xi_1, \ldots, \Xi_s$  are zero mean independent random variables in a separable Hilbert space and  $\|\Xi_i\| \leq M$  for  $i = 1, \ldots, n$ , then

$$\mathbb{P}\left(\left\|\frac{1}{n}\sum_{i=1}^{n}\Xi_{i}\right\|>t\right)<2\exp\left(-\frac{nt^{2}}{2M^{2}}\right).$$

**Lemma G.2.** We have for all  $j = 1, \ldots, s$ ,

(G.1) 
$$\mathbb{E}\left[\|\Delta f^{(j)}\|_{\mathcal{H}}^2 \,|\, \mathbb{U}\right] \le 2\sigma^2/\lambda + 4\|f_0\|_{\mathcal{H}}^2.$$

PROOF. By the zero order optimality condition, we have

$$\begin{split} \lambda \|\widehat{f}^{(j)}\|_{\mathcal{H}}^2 &\leq \frac{1}{n} \sum_{i \in L_j} (Y_i - \widehat{m}^{(j)}(U_i))^2 + \lambda \|\widehat{f}^{(j)}\|_{\mathcal{H}}^2 \\ &\leq \frac{1}{n} \sum_{i \in L_j} (Y_i - m_0^{(j)}(U_i))^2 + \lambda \|f_0\|_{\mathcal{H}}^2 \\ &= \frac{1}{n} \sum_{i \in L_j} \varepsilon_i^2 + \lambda \|f_0\|_{\mathcal{H}}^2. \end{split}$$

Hence taking expectation conditioned on  $\mathbb{U}$ , we get

$$\lambda \mathbb{E}[\|\widehat{f}^{(j)}\|_{\mathcal{H}}^2 \,|\, \mathbb{U}] \le \sigma^2 + \lambda \|f_0\|_{\mathcal{H}}^2.$$

Then, applying triangular inequality along with the inequality  $(a+b)^2 \leq 2a^2 + 2b^2$ , we have

$$\mathbb{E}[\|\Delta f^{(j)}\|_{\mathcal{H}}^{2} | \mathbb{U}] \leq 2\|f_{0}\|_{\mathcal{H}}^{2} + 2\mathbb{E}[\|\widehat{f}^{(j)}\|_{\mathcal{H}}^{2} | \mathbb{U}]$$
  
$$\leq \frac{2\sigma^{2}}{\lambda} + 4\|f_{0}\|_{\mathcal{H}}^{2},$$

as desired.

**Lemma G.3** (Matrix Heoffding in Tropp (2012)). Consider a finite sequence  $\{\mathbf{A}_i\}_{i=1}^n$  of independent, random, symmetric matrices with dimension p. Assume that each random matrix satisfies

$$\mathbb{E}[\mathbf{A}_i] = \mathbf{0}$$
 and  $\|\mathbf{A}_i^2\| \leq M$  almost surely.

Then, for all t > 0,

$$\mathbb{P}\Big(\Big\|\frac{1}{n}\sum_{i=1}^{n}\mathbf{A}_{i}\Big\| \ge t\Big) \le p\exp\Big(-\frac{nt^{2}}{8M}\Big).$$

**Lemma G.4.** Let  $\mathbf{A}, \mathbf{E} \in \mathbb{R}^{k \times k}$  be given. If  $\mathbf{A}$  is invertible, and  $\|\mathbf{A}^{-1}\mathbf{E}\| < 1$ , then  $\widetilde{\mathbf{A}} := \mathbf{A} + \mathbf{E}$  is invertible, and

$$\|\widetilde{\mathbf{A}}^{-1} - \mathbf{A}^{-1}\| \le \frac{\|\mathbf{E}\| \|\mathbf{A}^{-1}\|^2}{1 - \|\mathbf{A}^{-1}\mathbf{E}\|}$$

PROOF. See Theorem 2.5, p. 118 in Stewart and Sun (1990).

DEPARTMENT OF OPERATIONS RESEARCH AND FINANCIAL ENGINEERING PRINCETON UNIVERSITY PRINCETON, NEW JERSEY 08544 USA E-MAIL: tianqi@princeton.edu hanliu@princeton.edu DEPARTMENT OF STATISTICS PURDUE UNIVERSITY WEST LAFAYETTE, IN 47906 USA E-MAIL: chengg@purdue.edu