

Supplementary material for ‘Kernel-based covariate functional balancing for observational studies’

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5

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S1. PROOFS AND TECHNICAL RESULTS

S1.1. Proof of Proposition 1

10

Proof of Proposition 1. Consider any $v_1, v_2 \in \mathbb{R}^r$, and $t \in [0, 1]$. For $\beta \in \mathbb{R}^r$,

$$\begin{aligned} \beta^T \{ [tv_1 + (1-t)v_2] \{ tv_1 + (1-t)v_2 \}^T + B \} \beta &= [\{ tv_1 + (1-t)v_2 \}^T \beta]^2 + \beta^T B \beta \\ &= \{ tv_1^T \beta + (1-t)v_2^T \beta \}^2 + \beta^T B \beta \\ &\leq t(v_1^T \beta)^2 + (1-t)(v_2^T \beta)^2 + \beta^T B \beta \\ &= t\beta^T (v_1 v_1^T + B) \beta + (1-t)\beta^T (v_2 v_2^T + B) \beta \end{aligned}$$

15

Therefore, $\sigma_{\max} \{ [tv_1 + (1-t)v_2] \{ tv_1 + (1-t)v_2 \}^T + B \} \leq t\sigma_{\max}(v_1 v_1^T + B) + (1-t)\sigma_{\max}(v_2 v_2^T + B)$. \square

S1.2. Proof of Theorems 1 and 2

We begin with several definitions that will be used throughout the theoretical development. Write $w^* = (w_1^*, \dots, w_N^*)^T = [\{ \pi(X_1) \}^{-1}, \dots, \{ \pi(X_N) \}^{-1}]^T$ and

$$F_{N, \lambda_1, \lambda_2}(w) = \sup_{u \in \tilde{\mathcal{H}}_N} \{ S_N(w, u) - \lambda_1 \|u\|_{\mathcal{H}}^2 \} + \lambda_2 V_N(w).$$

Obviously $w^* \geq 1$. Due to the definition of the proposed estimator, we have $F_{N, \lambda_1, \lambda_2}(\hat{w}) \leq F_{N, \lambda_1, \lambda_2}(w^*)$. This implies that for any $f \in \tilde{\mathcal{H}}_N$,

$$S_N(\hat{w}, f) - \lambda_1 \|f\|_{\mathcal{H}}^2 + \lambda_2 V_N(\hat{w}) \leq S_N(w^*, u^*) - \lambda_1 \|u^*\|_{\mathcal{H}}^2 + \lambda_2 V_N(w^*), \quad (\text{S1})$$

where $u^* = \operatorname{argmin}_{u \in \tilde{\mathcal{H}}_N} \{ S_N(w^*, u) - \lambda_1 \|u\|_{\mathcal{H}}^2 \}$ and its existence is shown in §2.3. Since $S_N(\hat{w}, u) = 0$ for any $u \in \mathcal{H}$ such that $\|u\|_N = 0$, (S1) also implies that, for any $u \in \mathcal{H}$,

$$S_N(\hat{w}, u) - \lambda_1 \|u\|_{\mathcal{H}}^2 + \lambda_2 V_N(\hat{w}) \|u\|_N^2 \leq \{ S_N(w^*, u^*) - \lambda_1 \|u^*\|_{\mathcal{H}}^2 + \lambda_2 V_N(w^*) \} \|u\|_N^2. \quad (\text{S2})$$

In below, we adopt several choices of $f \in \tilde{\mathcal{H}}_N$ in (S1) and $u \in \mathcal{H}$ in (S2) to obtain various results. For instance, one obvious candidate of $f \in \tilde{\mathcal{H}}$ is the constant function z where $z(x) \equiv 1$. On the other hand, the control of $S_N(w^*, u^*)$ is given in the following Lemma S1, whose proof is given in §S1.4, so as to control the right-hand side of (S1) and (S2).

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LEMMA S1. *Suppose Assumptions 1 and 2 hold. Let $w^* = (w_1^*, \dots, w_N^*)^\top = [\{\pi(X_1)\}^{-1}, \dots, \{\pi(X_N)\}^{-1}]^\top$. There exists a constant $c \geq 0$ such that for all $T \geq c$,*

$$\text{pr} \left\{ \sup_{u \in \tilde{\mathcal{H}}_N} \frac{N S_N(w^*, u)}{\|u\|_{\mathcal{H}}^{d/\ell}} \geq T^2 \right\} \leq c \exp\left(-\frac{T^2}{c^2}\right).$$

30 Moreover, by central limit theorem, $V_N(w^*) = V + O_p(N^{-1/2})$ where $V = E\{\pi(X_1)^{-1}\}$. To prove Theorem 1, it suffices to establish the following two lemmas (Lemmas S2 and S3). The proof is given in §S1.4.

LEMMA S2. *Suppose Assumptions 1 and 2 hold. If $\lambda_1 \asymp N^{-1}$ and $\lambda_2 \asymp N^{-1}$, we have $S_N(\widehat{w}, z) = O_p(N^{-1})$ and $V_N(\widehat{w}) = O_p(1)$. Moreover, there exists a constant $W > 0$ such that*
 35 $E\{V_N(\widehat{w})\} \leq W$.

Proof of Lemma S2. Taking f as z (constant function of value 1) in (S1), we obtain a basic inequality:

$$S_N(\widehat{w}, z) + \lambda_1 \|u^*\|_{\mathcal{H}}^2 + \lambda_2 V_N(\widehat{w}) \leq S_N(w^*, u^*) + \lambda_1 \|z\|_{\mathcal{H}}^2 + \lambda_2 V_N(w^*). \quad (\text{S3})$$

By Lemma S1, there exists a constant c such that for all $T \geq c$, $\text{pr}\{S_N(w^*, u^*) \leq T^2 N^{-1} \|u^*\|_{\mathcal{H}}^{d/\ell}\} \geq 1 - c \exp(-T^2/c^2)$.

40 Let $\widetilde{E}_{N,1}$, $\widetilde{E}_{N,2}$ and $\widetilde{E}_{N,3}$ be the events that $S_N(w^*, u^*)$ is the largest in right-hand side of (S3), that $\lambda_1 \|z\|_{\mathcal{H}}^2$ is the largest in right-hand side of (S3), and that $\lambda_2 V_N(w^*)$ is the largest in right-hand side of (S3), respectively. Note that they are not necessarily disjoint. We write $E_{N,1} = \widetilde{E}_{N,1}$, $E_{N,2} = \widetilde{E}_{N,2} \setminus \widetilde{E}_{N,1}$ and $E_{N,3} = \widetilde{E}_{N,3} \setminus (\widetilde{E}_{N,1} \cup \widetilde{E}_{N,2})$. Therefore $\{E_1, E_2, E_3\}$ forms a partition of the sample space. We can further divide the event $E_{N,1}$ into two disjoint events, $E_{N,1,T} =$
 45 $E_{N,1} \cap \{S_N(w^*, u^*) \leq T^2 N^{-1} \|u^*\|_{\mathcal{H}}^{d/\ell}\}$ and $\check{E}_{N,1,T} = E_{N,1} \cap \{S_N(w^*, u^*) > T^2 N^{-1} \|u^*\|_{\mathcal{H}}^{d/\ell}\}$. Note that $\{E_{N,1,T} \cup \check{E}_{N,1,T} \cup E_{N,2} \cup E_{N,3}\}$ forms a partition of the sample space. We analyze (S3) on these events.

Case (i): On $E_{N,1,T}$, (S3) leads to $S_N(\widehat{w}, z) \leq T^{4d/(2\ell-d)} \lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)}$, $\|u^*\|_{\mathcal{H}} \leq T^{2\ell/(2\ell-d)} \lambda_1^{-\ell/(2\ell-d)} N^{-\ell/(2\ell-d)}$ and $\lambda_2 V_N(\widehat{w}) \leq T^{4d/(2\ell-d)} \lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)}$.

50 Case (ii): On $E_{N,2}$, (S3) leads to $S_N(\widehat{w}, z) \leq 3\lambda_1 \|z\|_{\mathcal{H}}^2$, $\|u^*\|_{\mathcal{H}} \leq 3\|z\|_{\mathcal{H}}$ and $\lambda_2 V_N(\widehat{w}) \leq 3\lambda_1 \|z\|_{\mathcal{H}}^2$.

Case (iii): On $E_{N,3}$, (S3) leads to $S_N(\widehat{w}, z) \leq 3\lambda_2 V_N(w^*)$, $\lambda_1 \|u^*\|_{\mathcal{H}}^2 \leq 3\lambda_2 V_N(w^*)$ and $\lambda_2 V_N(\widehat{w}) \leq 3\lambda_2 V_N(w^*)$.

Now, we focus on $S_N(\widehat{w}, z)$:

$$\begin{aligned} & \text{pr} \left[S_N(\widehat{w}, z) \leq \max \left\{ T^{4d/(2\ell-d)} \lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)}, 3\lambda_1 \|z\|_{\mathcal{H}}^2, 3\lambda_2 V_N(w^*) \right\} \right] \\ &= \sum_{i=1}^3 \text{pr} \left[S_N(\widehat{w}, z) \leq \max \left\{ T^{4d/(2\ell-d)} \lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)}, 3\lambda_1 \|z\|_{\mathcal{H}}^2, 3\lambda_2 V_N(w^*) \right\} \cap E_{N,i} \right] \\ &\geq \text{pr}(E_{N,1,T}) + \text{pr} \left[\left\{ S_N(\widehat{w}, z) \leq T^{4d/(2\ell-d)} \lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)} \right\} \cap \check{E}_{N,1,T} \right] + \text{pr}(E_{N,2}) + \text{pr}(E_{N,3}) \\ & \hspace{15em} (\text{S4}) \\ &= 1 - \text{pr} \left[\left\{ S_N(\widehat{w}, z) > T^{4d/(2\ell-d)} \lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)} \right\} \cap \check{E}_{N,1,T} \right] \end{aligned}$$

$$\begin{aligned} &\geq 1 - \text{pr}\{\check{E}_{N,1,T}\} \geq 1 - \text{pr}\{S_N(w^*, u^*) > T^2 N^{-1} \|u^*\|_{\mathcal{H}}^{d/\ell}\} = \text{pr}\{S_N(w^*, u^*) \leq T^2 N^{-1} \|u^*\|_{\mathcal{H}}^{d/\ell}\} \\ &\geq 1 - c \exp(-T^2/c^2), \end{aligned} \quad 60$$

for all $T \geq c$, where (S4) follows from the above analyses of Cases (i), (ii) and (iii). We can show that $N^{1/2}\{V_N(w^*) - V\}$ converges to $N(0, \sigma_V^2)$ in distribution by central limit theorem, where $V = E[\{\pi(X_1)\}^{-1}] < \infty$ and $\sigma_V^2 = \{1 - \pi(X_1)\}/\pi(X_1)^3 < \infty$. Therefore $S_N(\widehat{w}, z) = O_p(N^{-1})$ under the condition that $\lambda_1 \asymp N^{-1}$ and $\lambda_2 = O(N^{-1/2})$. If $\lambda_1 \asymp N^{-1}$ and $\lambda_2 \asymp N^{-1}$, similar arguments lead to $V_N(\widehat{w}) = O_p(1)$. 65

Now, we focus on $E\{V_N(\widehat{w})\}$ under $\lambda_2 > 0$. The requirements that $\lambda_1 \asymp N^{-1}$ and $\lambda_2 \asymp N^{-1}$ imply $\widetilde{B}_1 N^{-1} \leq \lambda_1 \leq B_1 N^{-1}$ and $\widetilde{B}_2 N^{-1} \leq \lambda_2 \leq B_2 N^{-1}$ for some positive constants $\widetilde{B}_1, B_1, \widetilde{B}_2$ and B_2 . We derive bounds for each term in the following decomposition of $E\{V_N(\widehat{w})\}$:

$$E\{V_N(\widehat{w}) | E_{N,1}\} \text{pr}(E_{N,1}) + E\{V_N(\widehat{w}) | E_{N,2}\} \text{pr}(E_{N,2}) + E\{V_N(\widehat{w}) | E_{N,3}\} \text{pr}(E_{N,3}).$$

The first term: Fix $\widetilde{c} = \max\{c, 2\widetilde{B}_1^{-d/(2\ell-d)}\widetilde{B}_2^{-1}, 2\}$ and $a > 0$ such that $\widetilde{c} > \widetilde{B}_1^{-d/(2\ell-d)}\widetilde{B}_2^{-1}c^{4da/(2\ell-d)}$ and $4da/(2\ell-d) < 1$. That means, a is a constant fulfilling $\min[(2\ell-d)\log\{\widetilde{c}\widetilde{B}_1^{d/(2\ell-d)}\widetilde{B}_2\}/4d \log \widetilde{c}, (2\ell-d)/4d] > a > 0$. 70

$$\begin{aligned} E\{V_N(\widehat{w}) | E_{N,1}\} \text{pr}(E_{N,1}) &= \int_0^\infty \text{pr}\{V_N(\widehat{w}) > t | E_{N,1}\} \text{pr}(E_{N,1}) dt \\ &= \int_0^\infty \text{pr}\{V_N(\widehat{w}) > t\} \cap E_{N,1} dt \\ &\leq \widetilde{c} + \int_{\widetilde{c}}^\infty \text{pr}\{V_N(\widehat{w}) > t\} \cap E_{N,1,t^a} dt + \int_{\widetilde{c}}^\infty \text{pr}\{V_N(\widehat{w}) > t\} \cap \check{E}_{N,1,t^a} dt \end{aligned}$$

Due to the construction of a ,

$$\int_{\widetilde{c}}^\infty \text{pr}\{V_N(\widehat{w}) > t\} \cap E_{N,1,t^a} dt \leq \int_{\widetilde{c}}^\infty \text{pr}\{t^{4da/(2\ell-d)}\widetilde{B}_1^{-d/(2\ell-d)}\widetilde{B}_2^{-1} \geq V_N(\widehat{w}) > t\} dt = 0.$$

Now, we look at the last term

$$\int_{\widetilde{c}}^\infty \text{pr}\{V_N(\widehat{w}) > t\} \cap \check{E}_{N,1,t^a} dt \leq \int_{\widetilde{c}}^\infty \text{pr}(\check{E}_{N,1,t^a}) dt \leq \int_{\widetilde{c}}^\infty c \exp\left(\frac{-t^{2a}}{c^2}\right) dt = -c \frac{c^{1/a} \Gamma(1/2a, t^{2a}/c^2)}{2a} \Big|_{\widetilde{c}}^\infty,$$

which is bounded due to the fact that $\Gamma(s, x)/(x^{s-1}e^{-x}) \rightarrow 1$ as $x \rightarrow \infty$. Therefore $E\{V_N(\widehat{w}) | E_{N,1}\} \text{pr}(E_{N,1}) < \infty$. 80

The second term: As shown in Case (ii):

$$E\{V_N(\widehat{w}) | E_{N,2}\} \text{pr}(E_{N,2}) \leq 3B_1 \widetilde{B}_2^{-1} \|z\|_{\mathcal{H}}^2 < \infty$$

The third term: As shown in Case (iii):

$$E\{V_N(\widehat{w}) | E_{N,3}\} \text{pr}(E_{N,3}) \leq 3B_2 E\{V_N(w^*) | E_{N,3}\} \text{pr}(E_{N,3}) \leq 3B_2 E\{V_N(w^*)\} = B_2 V < \infty. \quad 85$$

Combining the above results, there exists a constant $W > 0$ such that $E\{V_N(\widehat{w})\} \leq W$. \square

LEMMA S3. *Suppose Assumptions 1-3 hold. If $\lambda_1 \asymp N^{-1}$ and $\lambda_2 = O(N^{-1})$, then $S_N(\widehat{w}, m) = O_p(N^{-1}) \|m\|_N^2$. Further, if $\lambda_2 \asymp N^{-1}$, there exists a constant $S^2 > 0$ such that $E\{NS_N(\widehat{w}, m)\} \leq S^2$.*

90 *Proof of Lemma S3.* Rearranging the terms in (S2), we obtain the basic inequality:

$$S_N(\widehat{w}, m) + \lambda_1 \|u^*\|_{\mathcal{H}}^2 \|m\|_N^2 + \lambda_2 V_N(\widehat{w}) \|m\|_N^2 \leq S_N(w^*, u^*) \|m\|_N^2 + \lambda_1 \|m\|_{\mathcal{H}}^2 + \lambda_2 V_N(w^*) \|m\|_N^2. \quad (\text{S5})$$

By Lemma S1, we have $S_N(w^*, u^*) = O_p(N^{-1}) \|u^*\|_{\mathcal{H}}^{d/\ell}$. Now we compare different scenarios of (S5):

Case (i): Suppose that $S_N(w^*, u^*) \|m\|_N^2$ is the largest in right-hand side of (S5). If $\|m\|_N \neq 0$, we have $\|u^*\|_{\mathcal{H}} \leq \lambda_1^{-\ell/(2\ell-d)} O_p\{N^{-\ell/(2\ell-d)}\}$ and therefore
 95 $S_N(\widehat{w}, m) \leq \lambda_1^{-d/(2\ell-d)} O_p\{N^{-2\ell/(2\ell-d)}\} \|m\|_N^2$. As if $\|m\|_N = 0$, we have $S_N(\widehat{w}, m) = 0 \leq \lambda_1^{-d/(2\ell-d)} O_p\{N^{-2\ell/(2\ell-d)}\} \|m\|_N^2$.

Case (ii): Suppose that $\lambda_1 \|m\|_{\mathcal{H}}^2$ is the largest in right-hand side of (S5). We obtain $S_N(\widehat{w}, m) \leq 3\lambda_1 \|m\|_{\mathcal{H}}^2$.

Case (iii): Suppose that $\lambda_2 V_N(w^*) \|m\|_N^2$ is the largest in right-hand side of (S5). We obtain
 100 $S_N(\widehat{w}, m) \leq 3\lambda_2 \{V + O_p(N^{-1/2})\} \|m\|_N^2$.

Due to Lemma S7 in §S1.4, $\|m\|_N \leq R \|m\|_{\mathcal{H}} < \infty$. Overall, we have

$$S_N(\widehat{w}, m) = O_p \left[\max \left\{ \lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)} \|m\|_N^2, \lambda_1 \|m\|_{\mathcal{H}}^2, \lambda_2 \|m\|_N^2 \right\} \right].$$

Since $S_N(\widehat{w}, m) = 0$ if $\|m\|_N^2 = 0$, we have $S_N(\widehat{w}, m) = O_p(N^{-1}) \|m\|_N^2$ due to the conditions of λ_1 and λ_2 .

Next, suppose $\lambda_2 \asymp N^{-1}$. Based on the exponential inequality in Lemma S1, one could
 105 apply a similar argument of Lemma S2, and show that there exists a constant $\widetilde{S}^2 > 0$ such $E\{N^2 \widetilde{S}_N^2(\widehat{w}, m)\} \leq \widetilde{S}^2$ where

$$\widetilde{S}_N(\widehat{w}, m) = \begin{cases} S_N(\widehat{w}, m) / \|m\|_N, & \text{if } \|m\|_N \neq 0, \\ 0, & \text{if } \|m\|_N = 0. \end{cases}$$

Moreover,

$$\begin{aligned} E\{N S_N(\widehat{w}, m)\} &= E\{N \widetilde{S}_N(\widehat{w}, m) \|m\|_N^2\} \leq \frac{1}{2} \left[E\{N^2 \widetilde{S}_N^2(\widehat{w}, \widetilde{m})\} + E(\|m\|_N^4) \right] \\ &\leq \frac{1}{2} \left\{ \widetilde{S}^2 + \frac{\int m^4 dP}{N} + \frac{N-1}{N} \left(\int m^2 dP \right)^2 \right\} \\ &\leq \frac{1}{2} \left\{ \widetilde{S}^2 + \int m^4 dP + \left(\int m^2 dP \right)^2 \right\}. \end{aligned}$$

Due to Lemma S7 in §S1.4, $\int m^2 dP < \infty$ and $\int m^4 dP < \infty$. □

Proof of Theorem 2. Recall the decomposition:

$$\frac{1}{N} \sum_{i=1}^N T_i \widehat{w}_i Y_i = \frac{1}{N} \sum_{i=1}^N (T_i \widehat{w}_i - 1) m(X_i) + \frac{1}{N} \sum_{i=1}^N T_i \widehat{w}_i \varepsilon_i + \left[\frac{1}{N} \sum_{i=1}^N m(X_i) - E\{Y(1)\} \right] + E\{Y(1)\}.$$

Due to Lemma S7 in §S1.4, $\|m\|_2^2 = \int m^2 dP < \infty$. Since X_1, \dots, X_N are i.i.d., we can show that $\|m\|_N = \int m^2 dP + o_p(1)$. Therefore, the first term can be controlled:

115

$$\left| \frac{1}{N} \sum_{i=1}^N (T_i \widehat{w}_i - 1) m(X_i) \right| = S_N(\widehat{w}, m)^{1/2} = O_p(N^{-1/2}) \|m\|_2 + o_p(N^{-1/2}),$$

due to Theorem 1. Moreover, $E\{NS_N(\widehat{w}, m)\} < \infty$ due to Theorem 1. As for the second term, we write $\widehat{\delta}_i = T_i \widehat{w}_i$. Under Assumption 4, we have $E(\varepsilon_i \mid \widehat{\delta}_1, \dots, \widehat{\delta}_N) = 0$. Therefore,

$$\text{var} \left(\frac{1}{N} \sum_{i=1}^N T_i \widehat{w}_i \varepsilon_i \right) = E \left\{ \text{var} \left(\frac{1}{N} \sum_{i=1}^N \widehat{\delta}_i \varepsilon_i \mid \widehat{\delta}_1, \dots, \widehat{\delta}_N \right) \right\} \leq \frac{\sigma^2}{N} E\{V_N(\widehat{w})\} \leq \frac{\sigma^2 W}{N},$$

due to Theorem 1. Therefore, $N^{-1} \sum_{i=1}^N T_i \widehat{w}_i \varepsilon_i = O_p(N^{-1/2})$. The above derivation also implies that

120

$$E \left\{ N^{-1/2} \sum_{i=1}^N (T_i \widehat{w}_i - 1) \varepsilon_i \right\}^2 < \infty.$$

Finally, by central limit theorem, we have

$$\left[N^{-1} \sum_{i=1}^N m(X_i) - E\{Y(1)\} \right] = O_p(N^{-1/2}),$$

due to Assumption 4. Also,

$$E \left[N^{-1/2} \sum_{i=1}^N m(X_i) - E\{Y(1)\} \right]^2 < \infty.$$

Therefore, $\sum_{i=1}^N T_i \widehat{w}_i Y_i / N - E\{Y(1)\} = O_p(N^{-1/2})$ and $N^{1/2} [\sum_{i=1}^N T_i \widehat{w}_i Y_i / N - E\{Y(1)\}]$ has bounded variance. \square

S1.3. Proof of Theorem 3

125

LEMMA S4. *Suppose Assumptions 1 and 2 hold. Assume $\lambda_1 = O(N^{-1})$ and $\lambda_1^{-1} = o\{\lambda_2^{(2\ell-d)/d} N^{2\ell/d}\}$. We have $V_N(\widehat{w}) \leq V\{1 + o_p(1)\}$ where $V = E\{\{\pi(X_1)\}^{-1}\}$. Moreover, there exists a constant $W' > 0$ such that $E\{V_N(\widehat{w})\} \leq W'$.*

Proof of Lemma S4. Taking f as z (constant function of value 1) in (S1), we obtain the basic inequality:

130

$$S_N(\widehat{w}, z) + \lambda_1 \|u^*\|_{\mathcal{H}}^2 + \lambda_2 V_N(\widehat{w}) \leq S_N(w^*, u^*) + \lambda_1 \|z\|_{\mathcal{H}}^2 + \lambda_2 V_N(w^*), \quad (\text{S6})$$

for all large N such that $1 \leq BN^{1/3}$. By Lemma S1, $S_N(w^*, u^*) = O_p(N^{-1}) \|u^*\|_{\mathcal{H}}^{d/\ell}$. Moreover, it is easy to show that $V_N(w^*) = V + O_p(N^{-1/2})$. Due to the condition of λ_1 and λ_2 , we have $\lambda_1^{-d/(2\ell-d)} N^{-2\ell/(2\ell-d)} = o(\lambda_2)$ which implies $(\lambda_1 N)^{-d/(2\ell-d)} = o(\lambda_1^{-1} \lambda_2)$. As $\lambda_1 N = O(1)$, therefore $\lambda_1^{-1} \lambda_2 \rightarrow \infty$.

$$\lambda_1 \|z\|_{\mathcal{H}}^2 + \lambda_2 V_N(\widehat{w}) = \lambda_2 \{o(1) + V + O_p(N^{-1/2})\} = \lambda_2 V \{1 + o_p(1)\}.$$

135

Now, we come back to (S6). Let \mathcal{A} be the event that $S_N(w^*, u^*) \leq \lambda_1 \|z\|_{\mathcal{H}}^2 + \lambda_2 V_N(\widehat{w})$. On the event \mathcal{A}^c , from (S6), we obtain $\|u^*\|_{\mathcal{H}} \leq \lambda_1^{-\ell/(2\ell-d)} O_p\{N^{-\ell/(2\ell-d)}\}$ which implies

$S_N(\bar{w}, u^*) \leq \lambda_1^{-d/(2\ell-d)} O_p\{N^{-2\ell/(2\ell-d)}\} = o_p(\lambda_2)$ due to the conditions of λ_1 and λ_2 . Notice that, on \mathcal{A}^c , we also have $S_N(w^*, u^*) > \lambda_1 \|z\|_{\mathcal{H}}^2 + \lambda_2 V_N(\bar{w}) = \lambda_2 V\{1 + o_p(1)\}$. This implies that $\text{pr}(\mathcal{A}^c) \rightarrow 0$ as $N \rightarrow \infty$. Therefore we only have to focus on \mathcal{A} . From (S6), we obtain $\lambda_1 \|u^*\|_{\mathcal{H}}^2 \leq 2\lambda_2\{V + o_p(1)\}$. In this case, $\|u^*\|_{\mathcal{H}}^2 \leq 2\lambda_1^{-1}\lambda_2 V\{1 + o_p(1)\} = O_p(\lambda_1^{-1}\lambda_2)$. Therefore $S_N(w^*, u^*) = O_p(N^{-1})\|u^*\|_{\mathcal{H}}^{d/\ell} = O_p\{N^{-1}(\lambda_1^{-1}\lambda_2)^{d/(2\ell)}\} = o_p(\lambda_2)$. This implies that the right-hand side of (S6) is $\lambda_2 V\{1 + o_p(1)\}$. Hence $\lambda_2 V_N(\bar{w}) \leq \lambda_2 V\{1 + o_p(1)\}$. Finally, using a similar but simpler argument in Lemma S2, one can show that there exists a constant $W' > 0$ such that $E\{V_N(\bar{w})\} \leq W'$. \square

LEMMA S5. *Suppose Assumptions 1 and 2 hold. Let $h = m - \widehat{m} \in \mathcal{H}$ such that $\|h\|_N = o_p(1)$ and $\|h\|_{\mathcal{H}} = O_p(1)$. Further, assume $\lambda_1 = o(N^{-1})$, $\lambda_1^{-1}\|h\|_N^{2(2\ell-d)/d} = o_p(N)$ and $\lambda_2\|h\|_N^2 = o_p(N^{-1})$. Then $S_N(\bar{w}, h) = o_p(N^{-1})$. Moreover, there exists a constant $S' > 0$ such that $E\{NS_N(\bar{w}, h)\} \leq S'$.*

Proof of Lemma S5. Rearranging the terms in (S2), we obtain the basic inequality:

$$S_N(\bar{w}, h) + \lambda_1 \|u^*\|_{\mathcal{H}}^2 \|h\|_N^2 + \lambda_2 V_N(\bar{w}) \|h\|_N^2 \leq S_N(w^*, u^*) \|h\|_N^2 + \lambda_1 \|h\|_{\mathcal{H}}^2 + \lambda_2 V_N(w^*) \|h\|_N^2, \quad (\text{S7})$$

for all large N such that $C \leq BN^{1/3}$. The rest of the proof is similar to the proof of Lemma S3 but with different conditions of λ_1 and λ_2 . \square

Proof of Theorem 3. Recall the decomposition:

$$\begin{aligned} & \frac{1}{N} \sum_{i=1}^N T_i \bar{w}_i \{Y_i - \widehat{m}(X_i)\} + \frac{1}{N} \sum_{i=1}^N \widehat{m}(X_i) \\ &= \frac{1}{N} \sum_{i=1}^N (T_i \bar{w}_i - 1) h(X_i) + \frac{1}{N} \sum_{i=1}^N T_i \bar{w}_i \varepsilon_i + \left[\frac{1}{N} \sum_{i=1}^N m(X_i) - E\{Y(1)\} \right] + E\{Y(1)\}. \end{aligned}$$

Note that the assumed conditions imply the conditions of Lemmas S4 and S5. By Lemma S5, the first term of the decomposition is $o_p(N^{-1/2})$. By dominated convergence theorem, with Skorohod Representation Theorem to extend its result to weakly convergent sequence of random variables, we have $\text{var}\{N^{-1/2} \sum_{i=1}^N (T_i \bar{w}_i - 1) h(X_i)\} \leq E\{NS_N(\bar{w}, h)\} \rightarrow 0$ using Lemma S5. Write

$$Z_N = N^{1/2} \left(\frac{1}{N} \sum_{i=1}^N T_i \bar{w}_i \varepsilon_i + \left[\frac{1}{N} \sum_{i=1}^N m(X_i) - E\{Y(1)\} \right] \right).$$

It is obvious that $\text{var}(Z_N) = \text{var}\{m(X_1)\} + \sigma^2 E V_N(\bar{w})$. By Lemma S4, we have $\limsup_N E V_N(\bar{w}) \leq E\{V + o_p(1)\} = V$ using dominated convergence theorem.

Now, since the first term of the decomposition is $o_p(N^{-1/2})$, we focus on Z_N . We will utilize Theorem S1, by setting $\tau^2 = \text{var}\{m(X_1)\}$, $g^2(\mathcal{D}_N) = \sigma^2 V_N(\bar{w})$, and

$$A_j = \frac{m(X_j) - E\{Y(1)\}}{[N \text{var}\{m(X_1)\}]^{1/2}}, \quad \mathcal{B}_j = \{X_j, T_j\}, \quad C_j = \frac{T_j \bar{w}_j \varepsilon_j}{(\sigma^2 \sum_{i=1}^N T_i \bar{w}_i^2)^{1/2}}, \quad (j = 1, \dots, N).$$

Write $\mathcal{D}_N = \{A_1, \dots, A_N, \mathcal{B}_1, \dots, \mathcal{B}_N\}$. By the definition of \bar{w}_i ($i : T_i = 1$), $1 \leq \bar{w}_i \leq BN^{1/3}$ for all i . Therefore, $(\sum_{i=1}^N T_i \bar{w}_i^2)^{-1} = O_p(N)$ and $\max_i |\bar{w}_i| = o_p(N^{1/2})$. Moreover, $\max_i E|\varepsilon_i|^3 < \infty$ by

assumption. Hence

$$0 \leq E \left(\sum_{i=1}^N |C_i|^3 \mid \mathcal{D}_N \right) = \frac{(\max_i E|\varepsilon_i|^3) \sum_{j=1}^N T_j \tilde{w}_j^3}{\sigma^3 (\sum_{i=1}^N T_i \tilde{w}_i^2)^{3/2}} \leq \frac{(\max_i E|\varepsilon_i|^3) \max_i |\tilde{w}_i|}{\sigma^3 (\sum_{i=1}^N T_i \tilde{w}_i^2)^{1/2}} = o_p(1).$$

By Lemma S4, we have $E\{g^2(\mathcal{D}_N)\} \leq M$ and $g^2(\mathcal{D}_N) \leq M + o_p(1)$, by taking $M = \sigma^2 \max\{W', V\}$. Write

$$Z_n = \tau \sum_{j=1}^n A_j + g(\mathcal{D}_N) \sum_{j=1}^n C_j = N^{1/2} \left(\frac{1}{N} \sum_{i=1}^N T_i \tilde{w}_i \varepsilon_i + \left[\frac{1}{N} \sum_{i=1}^N m(X_i) - E\{Y(1)\} \right] \right)$$

$$Z_n^* = \tau F + g(\mathcal{D}_N) \sum_{j=1}^n \text{var}(C_j \mid \mathcal{D}_N)^{1/2} G_j = [\text{var}\{m(X_1)\}]^{1/2} F + \sigma N^{-1/2} \sum_{j=1}^N T_j \tilde{w}_j G_j$$

where F, G_1, \dots, G_N are i.i.d. standard normal random variables independent of C_1, \dots, C_N and \mathcal{D}_N . Let ϕ_N and ϕ_N^* be the corresponding characteristic function of Z_N and Z_N^* respectively. Applying Theorem S1, we have $|\phi_N(t) - \phi_N^*(t)| \rightarrow 0$ for every $t \in \mathbb{R}$ and ϕ_N^* is twice differentiable.

S1.4. Proof of Lemma S1

LEMMA S6. For $d/\ell < 2$, there exists a constant A such that the uniform entropy $H_\infty(\xi, \{u \in \mathcal{H} : \|u\|_{\mathcal{H}} \leq 1\}) \leq A\xi^{-d/\ell}$ for $\xi > 0$, where the uniform entropy is defined in Definition 2.3 of van de Geer (2000).

Proof of Lemma S6. This is shown by Birman & Solomyak (1967) and the fact that \mathcal{H} is a subspace of the Sobolev space $\mathcal{W}^{\ell,2}([0,1]^d)$. \square

LEMMA S7. There exists a constant R such that $\sup_{\{u \in \mathcal{H} : \|u\|_{\mathcal{H}} \leq 1\}} \|u\|_\infty \leq R$.

Proof of Lemma S7. This is due to Lemma 2.1 of Lin (2000) and norm equivalence. \square

Proof of Lemma S1. Let $\delta_i = T_i w_i^* - 1$. Note that the conditional expectation $E(\delta_i \mid X_i) = 0$. We will focus on the empirical process $\{N^{-1/2} \sum_{i=1}^N \delta_i u(X_i) : u \in \tilde{\mathcal{H}}\}$. Due to Assumption 1, $0 < w_i^* \leq C$ for all $i = 1, \dots, N$. Therefore, $\delta_i (i = 1, \dots, N)$ are uniformly sub-Gaussian: there exist constants K and σ_0^2 , independent of $X_i (i = 1, \dots, N)$, such that

$$\max_{i=1, \dots, N} K^2 \left[E \left(e^{|\delta_i|^2/K^2} \mid \{X_i\}_{i=1}^N \right) - 1 \right] \leq \sigma_0^2.$$

For instance, take $K = \max\{|C-1|, 1\}$ and $\sigma_0^2 = K^2(e-1)$, we have

$$K^2 \left[E \left(e^{|\delta_i|^2/K^2} \mid \{X_i\}_{i=1}^N \right) - 1 \right] \leq K^2(e-1) = \sigma_0^2.$$

To derive the modulus of continuity of the aforementioned empirical process, we need upper bound on the entropy results related to \mathcal{H} supplied by Lemma S6. Namely, under Assumption 2, there exists a constant A such that $H_\infty(\xi, \{u \in \mathcal{H} : \|u\|_{\mathcal{H}} \leq 1\}) \leq A\xi^{-d/\ell}$ for $\xi > 0$. Due to Lemma S7, there exists a constant R , independent of $X_i (i = 1, \dots, N)$, such that $\sup_{\{u \in \mathcal{H} : \|u\|_{\mathcal{H}} \leq 1\}} \|u\|_\infty \leq R$. Now, we apply Lemma 8.4 of van de Geer (2000). For some constant c depending on A, d, ℓ ,

195 R, K and σ_0 , we have for all $T \geq c$,

$$\text{pr} \left\{ \sup_{u \in \tilde{\mathcal{H}}_N} \frac{|N^{-1/2} \sum_{i=1}^N \delta_i u(X_i)|}{\|u\|_{\mathcal{H}}^{d/2\ell}} \geq T \mid X_1, \dots, X_N \right\} \leq c \exp\left(-\frac{T^2}{c^2}\right).$$

Note that the constant c is independent of $\{X_i\}$ which leads to the unconditional probability inequality that, for all $T \geq c$,

$$\text{pr} \left\{ \sup_{u \in \tilde{\mathcal{H}}_N} \frac{|N^{-1/2} \sum_{i=1}^N \delta_i u(X_i)|}{\|u\|_{\mathcal{H}}^{d/2\ell}} \geq T \right\} \leq c \exp\left(-\frac{T^2}{c^2}\right).$$

This implies the desired result. \square

S1-5. Partially Conditional Central Limit Theorem

200 **THEOREM S1.** *Let $(A_1, \mathcal{B}_1), \dots, (A_n, \mathcal{B}_n)$ be independent and identically distributed where A_1, \dots, A_n are random variables and $\mathcal{B}_1, \dots, \mathcal{B}_n$ are sets of random variables. Let $\{C_1, \dots, C_n\}$ be another set of random variables. Write $\mathcal{D}_n = \{A_1, \dots, A_n, \mathcal{B}_1, \dots, \mathcal{B}_n\}$. Assume these variables satisfy*

$$E(A_j) = 0, \quad E(C_j \mid \mathcal{D}_n) = 0, \quad (j = 1, \dots, n),$$

$$205 \quad \sum_{j=1}^n \text{var}(A_j) = 1, \quad \sum_{j=1}^n \text{var}(C_j \mid \mathcal{D}_n) = 1,$$

and there exists $\delta > 0$ such that $\sum_{j=1}^n E(|C_j|^{2+\delta} \mid \mathcal{D}_n) \rightarrow 0$ in probability. Moreover, C_1, \dots, C_n are conditionally independent given \mathcal{D}_n . Let g be a (non-random) function mapping from the support of \mathcal{D}_n to \mathbb{R}^+ such that there exists a constant $M > 0$ such that $Eg^2(\mathcal{D}_n) \leq M$ and $g^2(\mathcal{D}_n) \leq M + o_p(1)$. For any positive real number τ , consider two random variables:

$$Z_n = \tau \sum_{j=1}^n A_j + g(\mathcal{D}_n) \sum_{j=1}^n C_j \quad \text{and} \quad Z_n^* = \tau F + g(\mathcal{D}_n) \sum_{j=1}^n \{\text{var}(C_j \mid \mathcal{D}_n)\}^{1/2} G_j,$$

210 where F, G_1, \dots, G_n are i.i.d. standard normal random variables independent of C_1, \dots, C_n and \mathcal{D}_n . Let ϕ_n and ϕ_n^* be the corresponding characteristic function of Z_n and Z_n^* respectively. Then $|\phi_n(t) - \phi_n^*(t)| \rightarrow 0$ for every $t \in \mathbb{R}$. Moreover, $E(Z_n^{*2}) = \tau^2 + E\{g^2(\mathcal{D}_n)\} \leq \tau^2 + M$ and therefore ϕ_n^* is twice differentiable.

Proof of Theorem S1. We extend the arguments of Dvoretzky (1972) to our partially conditional setting. Let $F_1, \dots, F_n, G_1, \dots, G_n$ be i.i.d. standard normal random variables independent of C_1, \dots, C_n and \mathcal{D}_n . Write $\sigma_{C_j}^2(\mathcal{D}_n) = \text{var}(C_j \mid \mathcal{D}_n)$ for all $j = 1, \dots, n$. Throughout this proof, i represents the complex number such that $i^2 = -1$. Let $t \in \mathbb{R}$. First,

$$\exp \left\{ it \left(\tau \sum_{j=1}^n A_j + g(\mathcal{D}_n) \sum_{j=1}^n C_j \right) \right\} - \exp \left\{ it \left(\tau \sum_{j=1}^n n^{-1/2} F_j + g(\mathcal{D}_n) \sum_{j=1}^n \sigma_{C_j}(\mathcal{D}_n) G_j \right) \right\}$$

$$\begin{aligned}
&= \left(\exp \left[it \left\{ \tau \sum_{j=1}^n A_j + g(\mathcal{D}_n) \sum_{j=1}^n C_j \right\} \right] - \exp \left[it \left\{ \tau \sum_{j=1}^n A_j + g(\mathcal{D}_n) \sum_{j=1}^n \sigma_{C,j}(\mathcal{D}_n) G_j \right\} \right] \right) \\
&\quad + \left(\exp \left[it \left\{ \tau \sum_{j=1}^n A_j + g(\mathcal{D}_n) \sum_{j=1}^n \sigma_{C,j}(\mathcal{D}_n) G_j \right\} \right] - \exp \left[it \left\{ \tau \sum_{j=1}^n n^{-1/2} F_j + g(\mathcal{D}_n) \sum_{j=1}^n \sigma_{C,j}(\mathcal{D}_n) G_j \right\} \right] \right).
\end{aligned} \tag{220}$$

Denote the first bracket and the second bracket as Q_1 and Q_2 respectively. Write $\tilde{C}_k = g(\mathcal{D}_n) \sum_{j=1}^k C_j$ and $\tilde{G}_k = g(\mathcal{D}_n) \sum_{j=k+1}^n \sigma_{C,j}(\mathcal{D}_n) G_j$.

$$\begin{aligned}
Q_1 &= \exp \left(it \tau \sum_{j=1}^n A_j \right) \left\{ \exp(it \tilde{C}_n) - \exp(it \tilde{G}_0) \right\} \\
&= \exp \left(it \tau \sum_{j=1}^n A_j \right) \sum_{k=1}^n \left[\exp \{ it(\tilde{C}_k + \tilde{G}_k) \} - \exp \{ it(\tilde{C}_{k-1} + \tilde{G}_{k-1}) \} \right] \\
&= \exp \left(it \tau \sum_{j=1}^n A_j \right) \sum_{k=1}^n \exp \{ it(\tilde{C}_{k-1} + \tilde{G}_k) \} \left[\exp \{ itg(\mathcal{D}_n) C_k \} - \exp \{ itg(\mathcal{D}_n) \sigma_{C,k}(\mathcal{D}_n) G_k \} \right]
\end{aligned} \tag{225}$$

Therefore,

$$\begin{aligned}
&|E(Q_1)| \\
&\leq \sum_{k=1}^n \left| E \left(\exp \left(it \tau \sum_{j=1}^n A_j \right) E \left[\exp \{ it(\tilde{C}_{k-1} + \tilde{G}_k) \} \mid \mathcal{D}_n \right] \right. \right. \\
&\quad \left. \left. \times E \left[\exp \{ itg(\mathcal{D}_n) C_k \} - \exp \{ itg(\mathcal{D}_n) \sigma_{C,k}(\mathcal{D}_n) G_k \} \mid \mathcal{D}_n \right] \right) \right| \\
&\leq \sum_{k=1}^n E \left(\left| \exp \left(it \tau \sum_{j=1}^n A_j \right) \right| E \left[\left| \exp \{ it(\tilde{C}_{k-1} + \tilde{G}_k) \} \right| \mid \mathcal{D}_n \right] \right. \\
&\quad \left. \times \left| E \left[\exp \{ itg(\mathcal{D}_n) C_k \} - \exp \{ itg(\mathcal{D}_n) \sigma_{C,k}(\mathcal{D}_n) G_k \} \mid \mathcal{D}_n \right] \right| \right) \\
&\leq \sum_{k=1}^n E \left| E \left[\exp \{ itg(\mathcal{D}_n) C_k \} - \exp \{ itg(\mathcal{D}_n) \sigma_{C,k}(\mathcal{D}_n) G_k \} \mid \mathcal{D}_n \right] \right|
\end{aligned} \tag{S8}$$

Similarly,

$$\begin{aligned}
|E(Q_2)| &\leq \left| E \left[\exp \left\{ itg(\mathcal{D}_n) \sum_{j=1}^n \sigma_{C,k}(\mathcal{D}_n) G_j \right\} \left\{ \exp \left(it \tau \sum_{j=1}^n A_j \right) - \exp \left(it \tau \sum_{j=1}^n n^{-1/2} F_j \right) \right\} \right] \right| \\
&\leq \left| E \left\{ \exp \left(it \tau \sum_{j=1}^n A_j \right) - \exp \left(it \tau \sum_{j=1}^n n^{-1/2} F_j \right) \right\} \right|
\end{aligned} \tag{235}$$

$$\leq \sum_{k=1}^n \left| E \left\{ \exp(it\tau A_k) - \exp(it\tau n^{-1/2} F_k) \right\} \right|, \quad (\text{S9})$$

where the last inequality is due to a similar argument applied to Q_1 .

240 Now, we focus on (S8). As

$$\left| \exp(it) - \sum_{k=0}^K \frac{(it)^k}{k!} \right| \leq 2 \min \left\{ \frac{|t|^{n+1}}{(n+1)!}, \frac{2|t|^n}{n!} \right\}.$$

For any $\varepsilon > 0$,

$$\begin{aligned} & \sum_{k=1}^n \left| E \left[\exp \{ itg(\mathcal{D}_n)C_k \} \mid \mathcal{D}_n \right] - 1 + \frac{1}{2} t^2 g^2(\mathcal{D}_n) \sigma_{C,k}^2(\mathcal{D}_n) \right| \\ & \leq \frac{1}{6} |t|^3 \sum_{k=1}^n E \left[|g(\mathcal{D}_n)C_k|^3 I\{|g(\mathcal{D}_n)C_k| \leq \varepsilon\} \mid \mathcal{D}_n \right] + t^2 \sum_{k=1}^n E \left[g^2(\mathcal{D}_n) C_k^2 I\{|g(\mathcal{D}_n)C_k| > \varepsilon\} \mid \mathcal{D}_n \right] \\ & \leq \frac{1}{6} \varepsilon^3 |t|^3 + t^2 g^2(\mathcal{D}_n) \sum_{k=1}^n E \left[C_k^2 I\{|g(\mathcal{D}_n)C_k| > \varepsilon\} \mid \mathcal{D}_n \right]. \end{aligned}$$

245 Since $|g(\mathcal{D}_n)C_k| > \varepsilon$ implies $|g(\mathcal{D}_n)C_k/\varepsilon|^\delta > 1$, we have

$$\begin{aligned} 0 \leq g^2(\mathcal{D}_n) \sum_{k=1}^n E \left[C_k^2 I\{|g(\mathcal{D}_n)C_k| > \varepsilon\} \mid \mathcal{D}_n \right] & \leq \frac{g^{2+\delta}(\mathcal{D}_n)}{\varepsilon^\delta} \sum_{k=1}^n E \left[|C_k|^{2+\delta} I\{|g(\mathcal{D}_n)C_k| > \varepsilon\} \mid \mathcal{D}_n \right] \\ & \leq \frac{g^{2+\delta}(\mathcal{D}_n)}{\varepsilon^\delta} \sum_{k=1}^n E \left(|C_k|^{2+\delta} \mid \mathcal{D}_n \right), \end{aligned}$$

where the rightmost expression converges to 0 in probability, since $\sum_{k=1}^n E(|C_k|^{2+\delta} \mid \mathcal{D}_n) \rightarrow 0$ in probability and $g^2(\mathcal{D}_n) \leq M + o_p(1)$. Moreover,

$$g^2(\mathcal{D}_n) \sum_{k=1}^n E \left[C_k^2 I\{|g(\mathcal{D}_n)C_k| > \varepsilon\} \mid \mathcal{D}_n \right] \leq g^2(\mathcal{D}_n),$$

250 where $Eg^2(\mathcal{D}_n) \leq M$. By dominated convergence theorem, with Skorohod Representation Theorem to extend its result to weakly convergent sequence of random variables, we have $E(g^2(\mathcal{D}_n) \sum_{k=1}^n E[C_k^2 I\{|g(\mathcal{D}_n)C_k| > \varepsilon\} \mid \mathcal{D}_n]) \rightarrow 0$. As $\varepsilon > 0$ is arbitrary,

$$E \sum_{k=1}^n \left| E \left[\exp \{ itg(\mathcal{D}_n)C_k \} \mid \mathcal{D}_n \right] - 1 + \frac{1}{2} t^2 g^2(\mathcal{D}_n) \sigma_{C,k}^2(\mathcal{D}_n) \right| \rightarrow 0. \quad (\text{S10})$$

Similarly, we have

$$\begin{aligned}
& \sum_{k=1}^n \left| E \left[\exp \{ itg(\mathcal{D}_n)\sigma_{C,k}(\mathcal{D}_n)G_k \} \mid \mathcal{D}_n \right] - 1 + \frac{1}{2}t^2g^2(\mathcal{D}_n)\sigma_{C,k}^2(\mathcal{D}_n) \right| \\
& \leq \frac{1}{6}\varepsilon^3|t|^3 + t^2g^2(\mathcal{D}_n) \sum_{k=1}^n \sigma_{C,k}^2(\mathcal{D}_n) E \left[G_k^2 I \{ |g(\mathcal{D}_n)\sigma_{C,k}(\mathcal{D}_n)G_k| > \varepsilon \} \mid \mathcal{D}_n \right] \\
& \leq \frac{1}{6}\varepsilon^3|t|^3 + t^2 \frac{g^{2+\delta}(\mathcal{D}_n)}{\varepsilon^\delta} E \left(|G_1|^{2+\delta} \right) \sum_{k=1}^n \sigma_{C,k}^{2+\delta}(\mathcal{D}_n) \\
& \leq \frac{1}{6}\varepsilon^3|t|^3 + t^2 \frac{g^{2+\delta}(\mathcal{D}_n)}{\varepsilon^\delta} E \left(|G_1|^{2+\delta} \right) \sum_{k=1}^n E \left(|C_k|^{2+\delta} \mid \mathcal{D}_n \right)
\end{aligned} \tag{255}$$

where the last equality is due to Jensen's inequality as $(2 + \delta)/2 > 1$. As G_1 is a standard normal random variable, $E|G_1|^{2+\delta} = \Gamma\{(3 + \delta)/2\}\pi^{-1/2}$ where Γ is the Gamma function. Therefore $E|G_1|^{2+\delta} < \infty$. Hence, by a similar argument using dominated convergence theorem, we conclude

$$E \sum_{k=1}^n \left| E \left[\exp \{ itg(\mathcal{D}_n)\sigma_{C,k}(\mathcal{D}_n)G_k \} \mid \mathcal{D}_n \right] - 1 + \frac{1}{2}t^2g^2(\mathcal{D}_n)\sigma_{C,k}^2(\mathcal{D}_n) \right| \rightarrow 0.$$

Combining with (S10), $|E(Q_1)| \rightarrow 0$. Similar but simpler argument can be used to control (S9) and conclude that $|E(Q_2)| \rightarrow 0$. As a result,

$$\left| E \exp \left[it \left\{ \tau \sum_{j=1}^n A_j + g(\mathcal{D}_n) \sum_{j=1}^n C_j \right\} \right] - E \exp \left[it \left\{ \tau \sum_{j=1}^n n^{-1/2}F_j + g(\mathcal{D}_n) \sum_{j=1}^n \sigma_{C,j}(\mathcal{D}_n)G_j \right\} \right] \right| \rightarrow 0, \tag{265}$$

for every t . Write $F = \sum_{j=1}^n n^{-1/2}F_j$ which is a standard normal random variable. Note that $E\{\tau F + g(\mathcal{D}_n)\sum_{j=1}^n \sigma_{C,j}(\mathcal{D}_n)G_j\}^2 = \tau^2 + E\{g^2(\mathcal{D}_n)\} \leq \tau^2 + M$, and therefore the second moment exists. Hence the characteristic function of $\tau F + g(\mathcal{D}_n)\sum_{j=1}^n \sigma_{C,j}(\mathcal{D}_n)G_j$ is at twice differentiable. Hence we obtain the desired result. Note that F is independent of both G_1, \dots, G_n and \mathcal{D}_n . Hence we obtain the desired result. \square 270

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[Received x x. Revised x x]